Exploring customer market share dynamics of UK retail banks emerging from their adoption of sustainable business models

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Graduate Thesis

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Model and data available on request at
https://github.com/ivandenbent/thesis_sustainable_banking/

An electronic version of this master thesis is available at
https://repository.tudelft.nl/

"*Even if a scientific model, like a car, has only a few years to run before it is discarded, it serves its purpose for getting from one place to another.*"

David L. Wingate

Summary

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Digital challenger banks in the UK retail banking industry have caused unprecedented Personal Current Account (PCA) market share changes at the cost of traditional banks. This loss in competitive position prompted traditional bank managers to reconsider the way they operate, resulting in the commoditization of digital services till date. Now, the industry is faced with another potentially disruptive strategic innovation: sustainable business models. Adopting such a business model is, however, a complex decision for bank managers, as they need to ensure that the resources and capabilities of their bank align in an optimal manner to achieve competitive advantage. On the one hand, there is evidence in favor of sustainable business models as they have been associated with lower bank risk, better (financial) performance, and higher stakeholder value. In addition, consumers and policymakers increasingly expect UK retail banks to adopt a sustainable business model. On the other hand, there are also many uncertainties regarding the disruptive potential of sustainable business models - in part because there is no insight on how consumers might respond. Bank managers are thus faced with a dilemma on whether to change their business model at the cost of existing revenue for potential future profit.

In this study, we aimed to address these latter risks by providing insights into the mechanisms that underlie changes in the PCA market shares of UK retail banks and investigating what the future composition of the UK retail banking industry might entail when banks adopt sustainable business models. The UK retail banking industry is, however, a complex, open, uncertain, and dynamic multi-actor system in which the competitive position of banks depends on the strategic decisions of themselves and their competitors. As a consequence, there are many plausible future states of the system that can only be explored by the quantitative simulation of banks' interactions. Previous literature advising bank managers on the adoption of sustainable business models fail to do so.

Due to the lack of detailed data on the consumer response to sustainable business models, however, we could not employ existing market share models that generally rely on the statistical analysis of this detailed (time-series) data. As such, we developed a novel simulation model that used the language of game theory in the context of agent-based modeling (ABM) to understand the complexity of customer market share dynamics. Specifically, the model simulated the consumer choice of bank behavior in response to the strategical decision-making of 20 banks on a variety of topics (e.g., sustainability, digital capabilities) during a seven-year time period. Consequent to being the first model of its kind that allows the study of the disruptive potential of a strategic innovation, we note that the model is unique in its ability to (i) simulate the endogenous decision-making by the banks under study in response to the evolving state of the system, (ii) simultaneously include (potentially) competitive effects (i.e., customer switching volumes) and (potentially) market-expansive effects (i.e., PCA market growth), and (iii) systematically address system uncertainties.

Using exploratory modeling of 12,000 alternative future scenarios, we show that PCA market shares are quite robust (i.e., between 0.5-2% decrease) to different factors such as the customer switching volume, PCA market growth, consumer choice of bank behavior, and different types of sustainable banking implementation strategies (e.g. being a leader or follower). As to the mechanisms that do underlie the marginal changes in the market shares of UK retail banks, we identify a role for improved digital capabilities of mid-tier banks resulting in an improved competitive position of these banks. In addition, smaller specialized banks in the UK may capture some market share, but this growth is limited as serving more customer segments is associated with less overall satisfaction and a consequent potential decrease in market share. This trade-off means that the organic growth of smaller banks in the UK retail banking industry is limited. We furthermore show that low PCA market growth, low consumer preference towards banks' sustainable operations, and moderate to high consumer preference towards banks' service quality and digital services significantly contribute to limiting the market share decrease of big 4 banks to max.

0.7%. Finally, we also show that PCA market pressure is not sufficient for all UK retail banks to adopt a sustainable business model. As such, we conclude that sustainable business models are not directly associated with PCA market share dynamics and that they have a minimal disruptive potential.

While numerical inaccuracy limits confidence in the simulation model outputs, the findings of this study can be used to draw general policy directions for UK regulators and bank managers.

To regulators:

- Focus on increasing competition through unique new entrants, as increased switching volumes currently have little effect on dynamics in customer market shares due to too little competitive differentiation between retail banks;
- Introduce additional incentives for retail banks to adopt sustainable business models, as PCA market pressure alone is insufficient to introduce a sustainability transition in the UK retail banking industry within the next seven years;
- Facilitate consistent data collection on a number of bank KPIs and make this data publicly available to aid future research onto the competitive positions of banks by both regulators and the private sector.

To bank managers:

- Do not focus on building customer market share, as one will likely capture customers that open a secondary (or even tertiary) account which is often operated with a very low margin (if not at a loss);
- Redefine how the customer value proposition is designed, as sustainable business models might have non-tangible side effects such as more loyal and less price-sensitive customers;
- Set up specialized PCA products to focus on an underserved small customer segment to avoid competing with the bulk of PCA providers;
- Use monetary incentives to compensate for a lacking performance on sustainability, digital capabilities, or service quality, as these incentives effectively dampen the dynamics in customer market shares;
- To mid-tier managers, investigate the potential to capture market share, as this study indicates that a potential upswing in mid-tier market share is possible.

Finally, we urge bank managers to consider the ecological consequences of sustainable business models when designing their policies. Precisely because there is no direct link between sustainable business models and customer market share, one can adopt such a business model without fearing the competitive position. The plausibility of irreversible climate change does mean that investment in measures for dealing with these circumstances, and not just greenwashing, should be taken sooner rather than later. Future work should focus on facilitating such multi-objective decision-making for bank managers by extending the model KPIs (e.g., consumer deposits, sustainability metrics) and by improving the model structure to increase numerical accuracy.

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This thesis represents the end of my three-year period as a double-degree student in Nanobiology & Engineering and Policy Analysis at the TU Delft. During this period, I have gained extremely valuable knowledge on a wide variety of topics. But, degrees are not really degrees without some struggles. I stressed out, pulled all-nighters, questioned my life choices, and got my perseverance tested – nothing short of a true university experience. It is therefore not without those around me that these three years have been an incredibly valuable experience, and as such I want to take a moment to thank them.

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And last but not least, thank your reader, for showing interest in my work. I hope that you enjoy it and learn a thing or two about the complexities of customer market share dynamics in the UK retail banking industry, and what it will take to make this industry more sustainable.

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List of Abbreviations

ABM	**A**gent-**B**ased **M**odelling
BEIS	Department for **B**usiness, **E**nergy & **I**ndustrial **S**trategy
BSDC	**B**usiness & **S**ustainable **D**evelopment **C**ommission
CMA	**C**ompetition & **M**arkets **A**uthority
CS	**C**orporate **S**ustainability
CSR	**C**orporate **S**ocial **R**esponsibility
DBIS	**D**epartment for **B**usiness **I**novation & **S**kills
EMA	**E**xploratory **M**odelling and **A**nalysis
ESG	**E**nvironmental, **S**ocial, and **G**overnance
FCA	**F**inancial, **C**onduct **A**uthority
KPI	**K**ey, **P**erformance **I**ndicator
LV	**L**otka-**V**olterra
ODD	**O**verview, **D**esign concepts **D**etails
PCBS	**P**arliamentary **C**ommission on **B**anking **S**tandards
PCA	**P**ersonal **C**urrent **A**ccount
PRA	**P**rudential **R**egulation **A**uthority
PRIM	**P**atient **R**ule **I**nduction **M**ethod
PSR	**P**ayments **S**ystem **R**egulator
ROI	**R**eturn **o**n **I**nvestment
SDG	**S**ustainable **D**evelopement **G**oal
SMF	**S**ocial **M**arket **F**oundation
SQ	**S**ub-**Q**uestion
UK	**U**nited **K**ingdom
UKCSI	**U**nited **K**ingdom Consumer & **S**ervice **I**nstitude

List of Definitions

On the banking industry:

Business model	A business model comprises four key elements: (i) the value delivered to customers (e.g., customer segments, value proposition, what is sold and how it is sold), (ii) the value delivery (e.g., internal resources and processes as well as external partnerships), (iii) the generated revenue (e.g., the pricing model and forms of monetization), and (iv) the company's position in the industry (e.g., company role and relationships across the value chain) (Giesen et al., 2010).
Commoditization	The process by which a product or service that once was unique or innovative becomes generic and widely available.
Competition	A rivalry where two or more banks strive for a common goal which cannot be shared, i.e., one's gain is the other's loss. This goal might include market shares, scarce resources, or recognition
Corporate purpose	A statement that describes the identity of a company through explaining the philosophy behind the business model. It articulates how a company strives to harmonize profits with social accountability and responsibility.
Consumer	A person who purchases goods and services from a particular category (such as personal bank accounts) for personal use.
Consumer choice of bank behavior	The consumer habits and preferences that influence their decision-making towards a specific bank provider. This decision-making is additionally influenced by external factors such as social trends.
CR1 ratio	Measure of market concentration. Calculated as the market share of the largest firm within a consumer market.
CR4 ratio	Measure of market concentration. Calculated as the market share of the four largest firms within a consumer market.
Customer (retail)	Consumer affiliated with a specific (retail) bank by having a personal bank account at that particular bank.
Customer attrition	The loss of customers.
Disruptive potential	A disruptive innovation is one that displaces an established business model and shakes up the industry or one that creates a completely new industry.
ESG rating	Measure of a company's resilience to long-term company-induced environmental, social and governance (ESG) risks. Having a low (e.g. negative) rating indicates that a company has a relatively higher unmanaged exposure to e.g. inefficient resource use, employee infirmity, and board dependence than comparable companies.
Green credit financing	A type of financial service provided by banks to encourage borrowers to commit green investment and achieve sustainable development. Levers such as a lower borrowing rate are used.

Herfindahl-Hirschman Index (HHI)	Measure of market consolidation. Calculated as the sum of the square of company market shares. Using the HHI, we can classify markets into three types: (i) Un-concentrated markets (HHI <1,000), (ii) Moderately concentrated markets (1,000<HHI<2,000), and (iii) Highly concentrated (HHI >2,000). Unlike the CR1 and CR4 ratios, the HHI considers the relative size of the market shares and thereby presents a broader and more complex measure of market concentration.
Incumbent bank	A leader in the banking industry.
Market value	The price of shares that buyers are willing to pay in the present.
Personal Current Account (PCA)	*"PCA services comprise the provision of an account marketed to individuals rather than businesses, offering facilities to hold deposits, to receive and make payments by cheque and/or debit card, to use ATM facilities and to make regular payments by direct debit and/or standing order. Many PCAs also offer overdraft facilities, whether arranged or unarranged, which enable account holders to withdraw cash beyond the amount held in the account up to a specified amount"* (CMA, 2016).
Present value	The present value of a future sum of money given a specified rate of return. The present value dictates that money received in the future is worth less as an equal amount received in the present.
Primary bank account	The banking account designated by a consumer as being the main/first account of operation.
Retail banking	Banking that provides financial services such as checking and savings accounts, mortgages, personal loans, credit cards, and certificates of deposit to individual consumers.
Sustainability	Umbrella term for ESG initiatives.

On game theory:

Autonomous agent	A software entity that carries out some set of operations on behalf of a modeler but without any interference of that modeler. Instead, it bases its actions on some status of itself or its environment, and acts on it in pursuit of its own agenda.
Equilibrium	The point in the game where all players have made their (optimal) decision, leading to a specific game outcome being reached.
Entities	An entity is an object that maintains a separate, singular identifiable, and distinct existence. Within business contexts, an entity can be any organization structure that has its own goals and processes.
Game	Any set of circumstances that has a result dependent on the actions of two or more players.
Heterogeneous	Diverse in character or content.
Information set	The information available to a player at a given point in the game.
Payoff	The payout a player receives from arriving at a specific game outcome. The payoff may be a reward (i.e. positive) or punishment (i.e. negative).
Player	A strategic entity with the ability to make decisions within the context of the game.

Strategy	A complete plan of action that dictates a players' next move given the set of circumstances that might arise in the game.
Strategic decision	Each decision maker has to take into consideration how their choice will affect their competitors choice(s), and how their opponents choice will affect them.

On Modelling and simulation:

Aggregation level	Aggregate data, concepts, or variables are high-level representations that are composed from a multitude of individual data, concepts, or variables. They thereby often abstract out the complexities of the individual components by considering only the high-level implications.
Conceptual model	A representation of a system based on several concepts that help people know, understand, or simulate the subject that the conceptual model represents. The included concepts are often abstractions of things in the real world, whether physical or social.
Endogenous	Within the modeling context, an endogenous variable is one whose measure is determined by the model, and an endogenous change is a change in an endogenous variable that is either the response to an exogenous change that is imposed on the model or to other endogenous changes.
Exogenous	Within the modeling context, an exogenous variable is one whose measure is determined outside the model and is thus imposed on the model, and an exogenous change or trend is a change in an exogenous variable.
Exploratory modelling and Analysis	A research methodology that uses computational experiments to analyze complex and uncertain systems. It thereby allows for robust, model-based decision making against an variety of possible futures.
Future system	Every possible future manifestation of a current system. The correct future system cannot be prediction at the current point in time due to the future being uncertain.
Model boundary	The model boundary determined which variables and/or concepts are included in the simulation model (whether exogenous or endogenous) and which variables and/or concepts are excluded from the simulation.
Model outcomes	Different possible manifestations of the future system according to the simulation model.
System	A set of things working together as parts of an interconnecting network; a complex whole.
Scenario space	The range of all possible scenarios that an agent of a system can encounter while navigating dynamic environments.

Chapter 1

Introduction

In this chapter, we introduce the topic of this thesis. To this end, section 1.1 describes the research background, section 1.2 demarcates the research problem situation, and section 1.3 describes the motivation for studying this problem. In section 1.4, we present the findings of a literature review that identified core concepts of the proposed study. Based on this literature synthesis, we identify a knowledge gap in section 1.5 that provides the foundation for defining the research scope, main research question, sub-questions, and core objectives of this thesis. Finally, in section 1.6, we present a reading guideline for this thesis.

1.1 Background information

United Kingdom (UK) retail banks provide UK consumers with a way to safely deposit their money, have access to credit, and benefit from money-managing services (Beerli et al., 2004). An important aspect of the UK retail banking industry is therefore the consumer choice of bank, which determines the variety of services available to the consumer as well as banks' market shares (Martenson, 1985). For decades, these latter market shares have been stable (except from periods of crisis), and the few changes that occurred could be attributed to inorganic growth via mergers and acquisitions (FCA, 2022a; SMF, 2018).

Between 2018 and 2021, however, the customer market shares suddenly shifted organically by 8% towards multiple new entrants in the UK retail banking industry (FCA, 2022a). These new entrants thereby caused an unprecedented increase in competition within the industry (FCA, 2022a,c). The changes in customer market share, in turn, are the result of the new entrants pushing past traditional banking boundaries to effectively distinguish themselves from established banks (Cetorelli and Strahan, 2006; McKinsey, 2019). That is, they generally operate digital-only and tend to adopt a strong and innovative corporate purpose that entails providing customers with sustainable services that meet their underserved desires (Accenture, 2020).

As these so-called digital challenger banks caused value migration at the cost of traditional banks' market share, revenue, and margins, the traditional bank managers were prompted to reconsider the way they operate (Accenture, 2018). This, till date, is resulting in the commoditization of digital services like online banking, banking apps, and personalized spending advice (FCA, 2022a). As such, the transition to digital banking can be classified as a strategic disruptive innovation, as the latter describes the process by which a smaller company - usually with fewer resources - moves upmarket and challenges established companies to change their business model (Birnbaum, 2005; Charitou and Markides, 2003).

Now, the UK retail banking industry is faced with another potentially disruptive strategic innovation: the transition to sustainable banking. This type of banking can be classified as a strategic innovation, as its way of doing business is dictated by the ecological course in contradiction to the unconditional financial performance maximization of traditional and digital banking (Accenture, 2020; Payment & Banking, 2021; Valls Martínez et al., 2020). Sustainable banking thus requires bank managers to fundamentally change their business model. Changing a business model is, however, a complex decision as bank managers have to ensure that their business model aligns their resources and capabilities in an optimal manner to strike competitive advantage (Ranjith, 2016). That is, they need to select the right type of business model given the economic environment and emerging market opportunities (Giesen et al., 2010). As such, bank managers are currently unsure about the adoption of sustainable business models, but there is some evidence that these models will improve the competitive position of banks as both consumers and policy-makers increasingly expect banks to operate sustainably.

Regarding consumers, this expectation is reflected by a shift in the consumer choice of bank behavior. That is, this choice was usually influenced by a wide variety of "hard" factors such as price and product portfolio, but consumers have recently become more considerate of sustainability-related "soft" factors

(Accenture, 2020; Payments Authority, 2022). By 2019, consumers whose choice of bank was influenced by its sustainability controlled global banking revenues worth $300 billion (i.e., c.14% of the total global client driven revenues) (McKinsey, 2021). The shift in consumer behavior is due to consumers' increased awareness of issues such as climate change (Arslan et al., 2021), health care disparities (Dickman et al., 2017), unfair labor practices (Soni et al., 2021), inclusion (Grzybczyk, 2021), and data security (Stewart and Jürjens, 2018). COVID-19, in addition, has accelerated the behavior change by sparking consumer self-reflection in pursuit of a more fulfilled and self-improved life (Accenture, 2020).

Regarding the political arena, the topic of sustainability is increasingly addressed by regulatory measures (Chen and Chen, 2021; Lovell, 2019). The UK Prudential Regulation Authority (PRA), for instance, published its expectations for how banks should approach the financial risks from climate change (PRA, 2019). Policymakers even go so far as to argue that sustainable investing could be a potential mechanism for mitigating climate change (HM Treasury and BEIS, 2019; IPCC, 2018) and for realizing the United Nations' Sustainable Development Goals (SDGs) (Betti et al., 2018; Sánchez-Hernández et al., 2021). Besides addressing environmental problems, a shift to sustainable banking is also essential to prevent a global economic downturn of $30 trillion (BSDC, 2017). As such, facilitating a sustainability transition in the UK retail banking industry can be seen as a public incentive. Its importance to policymakers is supported by expected new (global) Environment, Social, and Governance (ESG) reporting rules, which *"possibly present the biggest regulatory change to the global banking system since the Basel Accord coming out of the 2008 banking crisis"* (Abbott, 2022).

The potentially disruptive effect of sustainable business models on traditional banks' market shares (as demonstrated by the previous digitalization transition) in combination with changing consumer behavior and upcoming regulations are thus forcing traditional banks to reconsider if they should adopt a sustainable business model (Accenture, 2020; McKinsey, 2019). In response, both corporate and academic literature have started to provide insights, best practices, and tools for bank managers to increase their sustainability and survive the new retail banking landscape (Accenture, 2020; McKinsey, 2019; Raut et al., 2017; Yip and Bocken, 2018). This advice is, however, mostly at the isolated retail bank level and thereby neglects the fact that retail banks operate within a competitive environment (Cooper, 1993; Marasco et al., 2016). The latter implies that a seemingly small change at the individual retail bank level can set into motion a cascade of events and grand outcomes that could affect other retail banks (Hopkins, 2018; Lorenz, 2000). We therefore argue that it is invalid to discuss the effect of adopting a sustainable business model on banks' competitive position without including the ecological economics that are set into motion by competitors.

1.2 Research problem situation

The UK retail banks have to align their business model into a coordinated program designed to drive revenue and profit, besides possible other objectives such as social and environmental sustainability (Charan, 2020; Lovell, 2019). Their upcoming decision towards the adoption of a sustainable business model thus influences their competitive position. The ensemble of all these decisions is expected to further change the market shares in the retail banking industry but, to the best of our knowledge, a study that provides insights into the legitimacy of those claims and as to what they might entail has not been done before (Accenture, 2020; Yip and Bocken, 2018). In this study, we therefore aim to unravel the mechanisms that underlie changes in the market shares of UK retail banks and investigate what the future composition of the UK retail banking industry might entail.

Doing so requires an understanding of the intensity and/or combination of certain variables that optimize the bank's competitive position. This, in turn, requires the understanding of how consumers respond to these variables (Charan, 2020). As such, this research benefits from a modelling approach in which the impact of the mix of variables on the polychotomous choice problem of consumer choice behavior can be assessed (de Andrade et al., 2010; Farooqui and Niazi, 2016). In this study, we therefore use a simulation model to investigate the dynamics in the market shares of retail banks that emerge from banks' transitions to sustainable banking.

1.3 Motivation for thesis

By studying the mechanisms that underlie changes in the market shares of retail banks, we aim to advise both bank managers and regulators on how to navigate the new retail banking landscape. This is because the problem at hand is partly an optimization problem for bank managers, in which we aim to advise on an optimal decision towards an unknown future regarding the adoption of a sustainable business model. Here, modeling advantageously allows for the generation of robust corporate policy advice by testing for different institutional arrangements that optimize against the different outcomes of the future system (Kwakkel and Pruyt, 2013). The simulation model thus helps to answer questions such as *"is being an innovator worth the risk?"*, *"Is it better to wait and learn from the experiences of the first entrant to the market?"*, and *"what is the proper balance between the risks and rewards?"* (Charitou and Markides, 2003). As such, bank managers can be better informed about the possible impacts of the strategic innovation and do not have to base their decision on the rearview mirror of the past (Thomond et al., 2003). The latter advantageously contributes to mitigating the uncertainty that incumbents bank managers are faced with by evaluating temporal sustainable banking implementation strategies without the risk of poor future performance. This is expected to facilitate banks' transitions to a sustainable business model, which, in turn, positively contributes to the SDGs and mitigating climate change. As such, this positive impact on the earth eventually benefits multiple stakeholders like consumers and environmental groups, which makes this research a solid fit with academia and society; the study is relevant for people, for the planet, for profit, and for science.

In addition, the insights that are gained into the dynamics of market shares could be used to educate regulators that need to get acquainted with the new retail banking landscape. Specifically, it is currently unknown how sustainable banking will impact the retail banking industry in the next decade, considering it has been suggested that the "innovation butterfly" is capable of single-handedly shaping an entire market (Hopkins, 2018; Liu, 2020; McKinsey, 2019). On the other hand, it might be that market pressure alone is not sufficient to incentivize the wide-spread adoption of sustainable business models in the UK retail banking industry, meaning that regulators will have to intervene if they want a sustainability transition in the UK retail banking industry. Anticipating on the future dynamics in the market shares and their underlying mechanisms therefore allows regulators to act before potential unwanted situations arise.

1.4 Literature Review

The purpose of this section is to provide an initial assessment of the state of the art on the subject of sustainable banking. Firstly, the initial review approach is outlined, followed by the definition of sustainable banking. Next, we describe the previous studies on the impact of sustainable business models. Finally, we review sustainable business models in the context of strategic disruptive innovations. The analysis of the literature is completed later on, as Chapters 2 and 3 cover the chosen modelling method and the retail banking industry in depth.

1.4.1 Literature review methodology

This literature review was conducted by following the method in Silyn-Roberts (2013). Peer-reviewed research articles were searched in databases Science Direct, Google Scholar, and SAGE Publishing Journals using the terms and phrases per core concept as defined in Table 1.1. We furthermore included gray literature such as company reports and press releases to account for the state-of-the-art of the retail banking industry. The latter were found by searching Google directly using the same terms and phrases. The search was limited to English written studies, with a historical limit of 2008 or more recent. This is due to the 2008 financial crisis, which drastically reshaped the banking industry including consumer opinions, thereby making findings from before 2008 less reliable (Bennett and Kottasz, 2012). Nevertheless, some older sources found through cross-references are included to understand historical developments. Papers were selected in terms of relevance to the core concepts, seeking to diversify perspectives to sustainable banking. Analysis of the titles and abstracts was central in forming this final selection. A total of 46 sources were synthesized for the review.

TABLE 1.1: The search criteria used to obtain sources for the literature review. 'Core concept' defines the criterion, 'relevance' explains why the core concept is crucial, and 'terms and phrases' states the keywords used in databases.

Core concept	**Relevance**	**Terms and phrases**
Definition of sustainable banking	The inherent meaning of the concept needs to be established.	'sustainable banking' | ('sustainability' OR 'CSR' OR 'ESG') AND ('bank' OR 'organization')

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Core concept	Relevance	Terms and phrases
Impacts of sustainable business models	Reviewing the previous work done on sustainable business models to get an overview of the previous strategic advice to bank managers and regulators concerning the topic of sustainable banking. In addition, this inventory of previous studies gives an idea of how sustainable banking currently influences the banking sector.	('ESG' OR 'sustainability') AND ('profit' OR 'performance')
Sustainable banking as an innovator's dilemma	Learn about the disruptive nature of the upcoming paradigm shirt to sustainability.	('innovator's dilemma' OR 'strategic disruptive innovation') AND 'impact' OR 'sustainability'

1.4.2 Definition of sustainable banking

According to the United Nations, sustainability can be defined as a societal goal with three dimensions: the economic, social, and environmental dimension (informally known as profit, people, and planet, or the so-called "triple bottom line") (Miller, 2020; UNESCO, 2015). These dimensions ought to be balanced in the pursuit of an improved quality of life. Sustainability is also often thought of as a long-term goal by which we aim to meet our own needs without compromising the ability of future generations to meet their own needs.

Sustainability is often defined and measured by the ESG pillars

While there may be some formal definition, there are inconsistencies in literature showing that sustainability remains quite a vaguely defined concept that is an umbrella term for all of a company's efforts to reduce its impact on the world. Indeed, a review of 209 articles on sustainability found that only 11.5% included a definition of sustainability (Moore et al., 2017). Synonyms for sustainability that are often used include Environment, Social, and Governance (ESG) and Corporate Sustainable Responsibility (CSR) (see Figure 1.1 for detailed definitions). Both these synonyms, however, are different from the concept of sustainability. On one hand, the ESG criteria are a tangible set of standard measures that investors use to screen companies that they could potentially invest in (Hassel and Semenova, 2013). ESG and sustainability have some similarities in that they address the environmental and social aspects, but the scope of ESG is wider than what is considered in sustainability by including the "governance" pillar. CSR, on the other hand, is a self-regulating business model where companies are more conscious of the impact they are having on the wider society whilst also making themselves more accountable to themselves, their stakeholders, and the public. While CSR thus sounds similar to sustainability, there are quite some differences, including it its vision, management, and drivers (Last, 2012). It must also be noted that CSR was one of the first ideas to make sustainability more tangible within corporates, and is nowadays often treated interchangeably with ESG (Gillan et al., 2021). The main difference is that CSR holds businesses accountable for their social commitments in a qualitative manner, while ESG helps quantify such social efforts (Forbes, 2021). As a result, the ESG pillars are most often used to define and measure sustainability, as can be observed from governments and current voluntary reporting of organizations (HM Treasury, 2021).

Sustainable banking definitions separate the "profit" dimension from sustainability

A review on corporate sustainability (CS) by Montiel and Delgado-Ceballos (2014) showed that *"the CS field is still evolving and different approaches to define, theorize, and measure CS have been used"*. Interestingly, they also found differences between the literature that targets scholars versus the one targeting practitioners. We made similar observations while conducting this literature review. That is, we find that gray literature generally describes sustainable banking - also referred to as value-based, purpose-driven, or ethical banking - as having a corporate purpose to *"do no harm"*, *"make a difference"*, or *"improve life quality"*, while also benefiting shareholders (Ecolytiq, 2020; Hollensbe et al., 2014; Rey et al., 2019; Schaffmeister et al., 2021). This suggests that sustainable banking, in contrast to sustainability, puts emphasis on a separation between the profit and the social and environmental dimensions. Academic literature, on the other hand, often defines sustainable banks as those that have made responsibility for the environment and society the core of their business and mission (Kocornik-Mina et al., 2021; Montiel and Delgado-Ceballos, 2014). The matter of profit is hardly touched upon. These observations are also in line with the use of ESG to quantify sustainability, as ESG does not include the profit dimension. While profit is thus officially contained within the notion of sustainability, the banking industry regards it as a separate factor of which the exact role is not agreed upon (Montiel and Delgado-Ceballos, 2014).

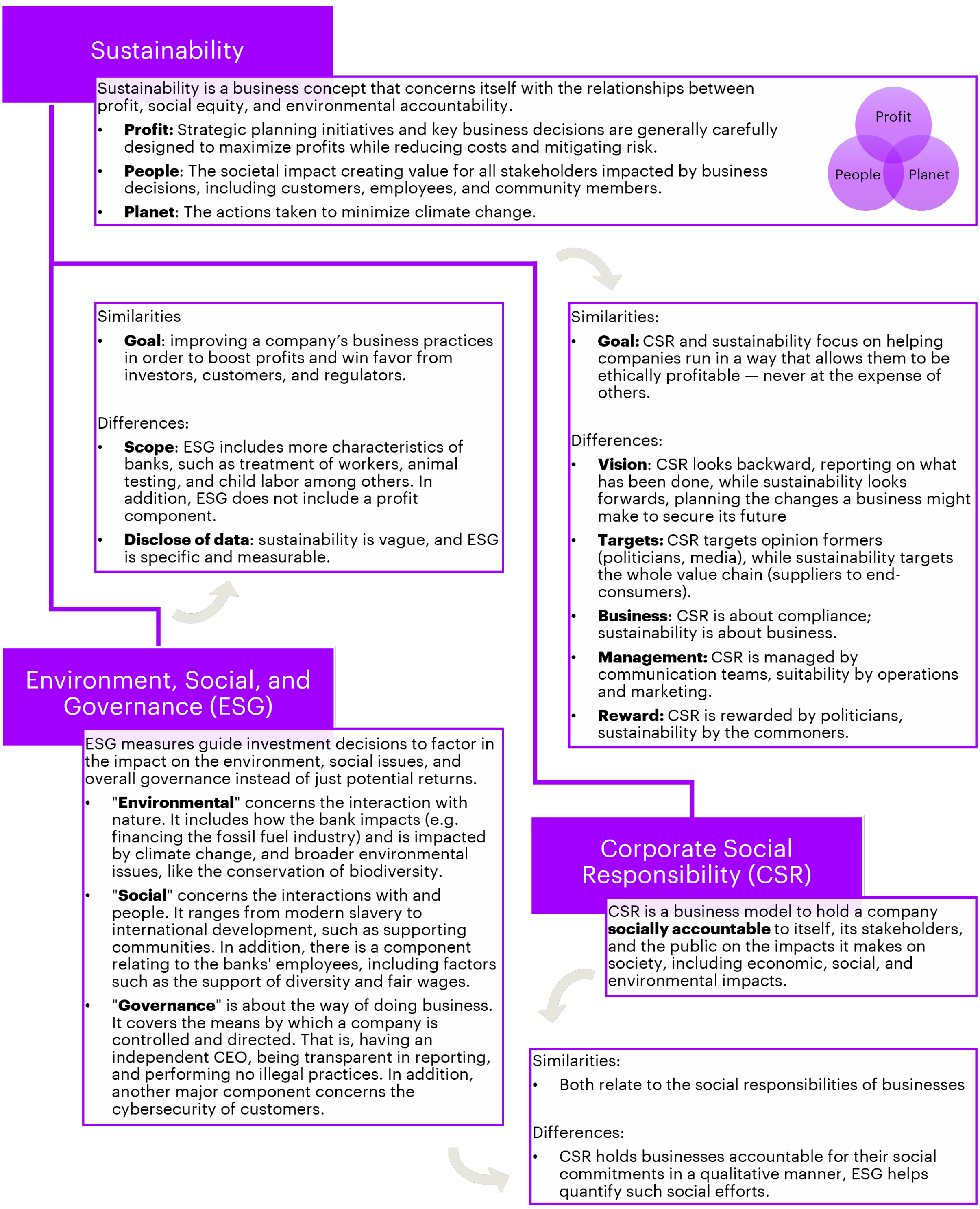

FIGURE 1.1: Definition, differences, and similarities between sustainability and its synonyms ESG and CSR.

1.4.3 Previous studies on the impact of sustainable business models

The rise of sustainable banking began when banks started to hold themselves accountable to society, accompanied by the rise of concepts such as ethical banking and CSR (Kocornik-Mina et al., 2021; Nosratabadi et al., 2020). This rise was timestamped to 2014 via a bibliometric examination and consequent ATLAS.ti content analysis of the literature on corporate social responsibility (CSR) (Sánchez-Hernández et al., 2021). Prior to 2014, most notions of sustainable banking conjured sentiments of trade-offs and charity – doing the right thing used to mean doing the less profitable thing (Ecolytiq, 2020). Most banks therefore instead assumed that with the right investments, talent, creativity, and strategic focus, they would evolve into digital-first banks with a growing profit (Accenture, 2019). And while indeed profits increased, this could only be attributed to a reduction in costs and not in revenue growth. Among the banks that did focus more on sustainability strategies, a consulting firm found that they did have increasing revenue, thereby identifying sustainability as a new growth area (Accenture, 2019).

Banks' sustainability profiles are associated with bank risk, performance, and value

After 2014, the attention on CS intensified as academic studies focused on proving to organizations that at least some forms of socially responsible behavior may actually improve the present value of a bank's future cash flow, and, thereby, may be consistent with the wealth-maximizing interest of its equity holders (Mackey et al., 2007). For instance, Laguir et al. (2018) showed that the environmental and financial performance are mutually reinforcing, although Jo et al. (2015) show that this enhanced return on bank assets generally takes one year to develop. Similarly, a positive correlation between financial performance and community involvement (social) (Simpson and Kohers, 2002) and corporate governance (Accenture, 2020; Esteban-Sanchez et al., 2017) was demonstrated. Banks' sustainability activities were furthermore demonstrated to correlate with the bank's market-, leadership-, and owner characteristics as well its risk, non-financial performance, and value (Gillan et al., 2021).

Increased consumer trust as mediator between sustainability and increased profit

As to explain the observations between sustainability and financial performance, literature suggests a role for consumer trust. It concludes that increasing sustainability practices has the added benefit of creating social goodwill, which, in turn, correlates with consumer trust (Accenture, 2020; Chernev and Blair, 2015). The latter seemingly presents itself as a "soft" factor, rich in emotional nuance, but is nevertheless of great influence in retail banking as it correlates with the purchase of more wealth-increasing products and more loyalty towards a brand (Accenture, 2020; Beerli et al., 2004; van Esterik-Plasmeijer and Van Raaij, 2017). Both these aspects substantially contribute to a sustained profit for the bank, as demonstrated by the 25% top trusted banks according to the Arabesque S-Ray Trust score having a 2.2 higher percentage point annual revenue growth rates (Accenture, 2020). As such, consumer trust is one of the most important assets in the retail banking industry (Rizan et al., 2014). In addition, increased ethical behavior by itself was demonstrated to attract additional customers (Mackey et al., 2007). What is more, Azmi et al. (2021) suggest customers of sustainable banks are less price-sensitive and there is thus more room for profit. That is, they value their banks' non-financial activities and hence are willing to accept lower deposit and higher borrowing rates. As such, sustainability, by implication, has become a driver of profit (through customers), meaning that there is also a corporate incentive to embrace the upcoming sustainability paradigm shift. And as consumer trust has been at an ongoing all-time low over the past decade, now is more than ever the time to gain competitive advantage mediated by increasing sustainability (Accenture, 2020; Järvinen, 2014; van Esterik-Plasmeijer and Van Raaij, 2017).

Being sustainable requires a bank to leverage its externalities to the good of the public

Besides the body of literature that tried to convince bank managers that sustainable business models could have a positive effect on their financial performance, we found quite some studies that advise banks on how they should execute their sustainable business model. Almost all studies tend to elaborate on the idea from Van den Bergh (2010) that sustainability is contained in the notion of so-called (environmental) "externalities". These externalities are an umbrella term for the impacts that a retail bank exerts on its surroundings - whether that be the environment, their customers, their employees, or even society at large - through its daily operations and the projects it funds (Laffont, 1989; Skinner, 2021). They imply that someone's utility (co)depends on factors beyond their control, but decided by retail banks. A well-known example is the sustained pollution due to continued financing of the fossil fuel industry (Bernardelli et al., 2022). Most literature is thus concerned with explaining that a sustainable business model requires a bank's externalities to be effectively leveraged to the good of the public (Liang and Reichert, 2012).

Multiple barriers currently prevent banks from adopting a sustainable business model

While theory thus suggests that sustainable banking is the "way-to-go", most banks are at an early stage of their sustainable journey, with no proven, tangible results for either themselves or their customers (Accenture, 2020; BSDC, 2017). Accenture (2021) identified four reasons explaining as to why sustainable banking might be held off: (i) banks do not believe that wide-scale disruption of the market is imminent, (ii) banks struggle with the classic innovator's dilemma on whether to sacrifice existing revenue for future profit or to focus on delivering shareholder returns, (iii) banks perceive the magnitude of the change to become truly sustainable as overwhelming, and (iv) there is no explicit mandate from regulators and government (yet). Future research should therefore focus on these barriers.

1.4.4 Sustainable banking as a strategic innovators dilemma

The rise of sustainable banking has analogies to a classic strategic innovator's dilemma (Birnbaum, 2005; Charitou and Markides, 2003). This dilemma discusses the implications of an innovator (usually a new entrant) which introduces a disruptive innovation that emphasizes a different product or service attributes. As a result, innovators become attractive to a new customer segment, thereby attacking a small part of the established incumbents' business. It is usually the part with low margins (due to little barriers to entry) that is attacked, which explains why established competitors often respond reluctantly. That is, they do not want to invest in defending their least profitable business and/or are afraid of cannibalizing their main business. As a result, the innovator is then able to capture a significant market share in that specific segment. During their growth, they improve to the extent that they are able to deliver performance that is sufficient in the old attributes that established competitors emphasize and superior in the new attributes. As innovators become more successful, they start to enter another market segment and the same thing happens, until incumbents take action or file for bankruptcy. At this point, the established competitors cannot afford to ignore the innovation and begin to consider ways to respond. This leads to an unavoidable realization: the new ways of doing business are in conflict with the established ways. That is because the strategic innovation has different key success factors and thus requires the bank to develop a new combination of tailored activities as well as new supporting cultures and processes. As sustainable banking requires banks to fundamentally shift their corporate purpose from financial performance to sustainable practices, sustainable banking can thus be viewed as a strategic innovator dilemma.

The impacts of strategic disruptive innovations are difficult to predict

This existence of trade-offs between "business as usual" banking and sustainable banking is making it difficult for an established bank to respond effectively. As such, the new entrants have been able to capture market share in the current account market, and now have started to expand their product portfolio and start to offer services like mortgages (McKinsey, 2019). The total impact of a strategic innovation (i.e., its disruptive potential) is, however, hard to predict (Birnbaum, 2005). This is even more so in existing markets, as the potential gains of a disruptive innovation from existing markets are very limited (Si and Chen, 2020). The new way of competing grows (usually quickly) to control a certain percentage of the market, but fails to overtake the traditional way completely. Internet banking, for instance, had grown rapidly in the first years after its introduction around the 2000s but had captured, at most, only 10% to 20% of the market by 2005. It was not until years later that it grew into the now common day-to-day service. Strategic innovations should therefore not be confused with technological innovations that often replace the existing technologies completely and destroy competitors that fail to adjust (Birnbaum, 2005). We also note that the definition of "disruptive innovation" is ambiguous, but is generally regarded as one that displaces an established business model and shakes up the industry or one that creates a completely new industry.

Barriers to the adoption of sustainable business models correspond to the barriers of incumbents to embrace strategic disruptive innovations

Previous research on the innovator's dilemma has mostly focused on which innovations have disruptive potential, as recognizing the latter is crucial for determining the response of incumbents. Giesen et al. (2010), for instance, address the when and how to innovate based on an identified set of characteristics that successful business model innovators demonstrate. That is, they find that a potentially dangerous innovator generally has three characteristics: (i) it aligns its core capabilities consistently across all dimensions of its business model to build customer value, (ii) it uses information strategically to create foresight, and prioritize actions while measuring and tracking for rapid course correction, and (iii) it operates adaptable with innovative leadership that allows a dynamic course correction. Indeed, we recognize that all these characteristics were common among the digital challenger banks when they gained market share and initiated the digitalization transition in the UK retail banking industry. On the other hand, Thomond et al. (2003) identified which barriers to embracing the disruptive innovation by incumbents exist and best-practices to overcome them. Intriguingly, these barriers largely overlap with the previously identified barriers to adopting a sustainable business model. That is, they showed that practitioners struggling to embrace the disruptive innovation suffer from one or a combination of some or all of the following inhibitors: (i) the strategic importance of the disruptive innovation is not understood, (ii) there is an inability to generate a disruptive concept within the existing business model, and (iii) there is a lack of funding towards the initiation of potentially disruptive projects. These observations thus give additional evidence that sustainable business models can be viewed as a potentially strategic disruptive innovation.

Previous research on innovator's dilemmas does hardly discuss sustainability

The literature on innovator dilemma's also generally distinguishes four types of disruptive innovations: a new product, a new technology to produce a product, a new way to distribute a product, and a new way to provide services. The latter can, for instance, be observed in the digitalization transition with the rise of banking apps and chatbots. Wang et al. (2022) is, however, the only to comment on the relationship between CSR (which is sustainability related) and innovation. Based on surveys of 226 high-tech firms and a consequent regression analysis, they demonstrate that the adoption of CSR practices is related to more incumbents embracing disruptive innovations, but that market turbulence negatively moderates this association. As such, the study does not classify sustainability as a potential strategic innovation, but rather argues that sustainability is a facilitator for other potentially disruptive innovations. Additional studies on the relationship between sustainability and disruptive innovation are rare and insufficient, leaving a deficiency that must be remedied (Ramani and Mukherjee, 2014).

The shift to sustainable banking corresponds to the shift from neoclassical to ecological economics

We argue that this gap in literature might be the consequence of sustainable banking being a more unique kind of innovator's dilemma. It is not one of the four typical innovations (e.g., a novel way of providing services), rather, it is providing something additional to the service; the transparency that sustainable banking brings empowers customers to change the world around them (Ecolytiq, 2020). In giving customers the chance to become stakeholders in sustainability issues, banks provide value-added services to their customers.

Doing so is in line with the shift from neoclassical to ecological economics. The former is based on the assumption that people make decisions in a cost-benefit manner and that there is perfect competition in markets, whereas the latter approaches the economy as both a social system, and as one constrained by the biophysical world (Gowdy and Erickson, 2005). That is, ecological economics dictates that understanding the context of economic activity requires familiarity with the relevant findings of related social and natural sciences (Pezzey and Toman, 2002). By implication, neoclassical economics hardly values sustainability as long as the carrying capacity of the environment is not exceeded, while ecological economics have sustainability as a core value by arguing that natural capital is only barely substitutable by other forms of capital. Sustainable banking can therefore be seen as an ecological economical way of doing business. According to Heckbert et al. (2010), as ecological economics phenomena concern the interactions among individuals, they have much to gain from computer modeling tools for complex systems. This latter finding is in line with our argumentation that it is invalid to discuss the effect of adopting a sustainable business model on banks' competitive position without including the ecological economics that are set into motion by competitors.

1.5 Knowledge gap

The literature review demonstrates that sustainable banks are often defined as those who have high ESG scores, thereby effectively decoupling profit from the concept of sustainability. Indeed, after sustainability was identified as a growth area for banks, many studies focused on establishing a relationship between sustainable banking and increased financial performance. The exact mechanism underlying this relation is, however, understudied, although consumers trust is found to play a role. Nevertheless, previous literature thus tends to regard sustainable banking as a driver of financial performance, thereby advising bank managers that there is a corporate incentive to embrace the upcoming sustainability paradigm shift. In response, there are also quite some studies that advise on the execution of a sustainable business model through leveraging a bank's externalities to the good of the public.

While there is thus a substantial body of literature advising that sustainable banking is the "way-to-go", many banks hold off the adoption of a sustainable business model. This is due to: (i) banks not believing that wide-scale disruption of the market is imminent, (ii) banks struggling with the classic innovator's dilemma on whether to sacrifice existing revenue for future profit or to focus on delivering shareholder returns, (iii) banks perceiving the magnitude of the change to become truly sustainable as overwhelming, and (iv) there being no explicit mandate from regulators and government (yet). Intriguingly, we found that these barriers correspond to previously identified barriers faced by incumbents when it comes to embracing strategic innovations. As such, and by analyzing the nature of sustainable banking in the context of innovators dilemmas, we found compelling evidence that sustainable business models can be regarded as a strategic innovation. There are, however, no previous academic studies on the disruptive potential of sustainable business models. We argue that this might be due to the complexity that would describe such a study, as (i) previous works on strategic disruptive innovations show that the impacts are hard to predict in general due to many uncertainties, and (ii) sustainable business models were found to be an ecological economics way of doing business, and as such should be studied by modeling the interactions among individuals to gain insight into the system behavior.

1.5.1 Research scope

We intend to address the knowledge gap on the disruptive potential of sustainable business models by modeling the future dynamics in UK retail banks' market shares. However, in line with lacking legitimacy as to the claims that further market share changes are imminent in the UK retail banking sector, a tangible definition of "market shares" was not available. We therefore synthesized multiple sources into finding a definition that is most relevant for the system under study.

Proposed mechanism underlying the relationship between sustainability and profit helps to define relevant market share

Market shares can concern value or volume, and we therefore needed to identify a variable that represents the impacts of sustainable business models on banks' competitive positions. To this end, we started by considering the relationship between sustainability and profit, which was demonstrated during the literature review to be subject to conflicting hypotheses and results regarding the underlying mechanisms (Gillan et al., 2021).

Specifically, based on the work of Accenture, we identified four pillars that positively contribute to a company's financial KPIs (see Figure 1.2) (Accenture, 2021). The included variables seemingly present a collection of KPIs that are not (directly) related by a common driver - yet work towards the same (financial) end. As such, we propose the following underlying mechanism supported by previously established variable relationships (see Figure 1.2): (1) sustainable banks have a better ability to attract talent as 75% of millennials would accept a lower salary to work for a socially responsible company (DaSilva, 2016); (2) Digitization skills are in short supply so recruiting and retaining skilled employees is essential to ensure high-quality digital services (Balsmeier and Woerter, 2019; Markovitch and Willmott, 2014); (3) Having a better (digital) product portfolio reinforces the attraction of talent as the majority of employees (72%) agree a company's digital leadership greatly influences their willingness to join an organization (Link, 2018); (4) increased ethical behavior attracts customers (Mackey et al., 2007); (5) Better digitization attracts customers including customers that may not be willing to switch purely from a sustainability perspective (Accenture, 2021); (6) Increased numbers of customers combined with wealth-increasing digital services for these customers lead to more profit for banks (Accenture, 2020); (7) Diversified digital products help banks to improve their performance and to remain competitive in the market (Abbasi and Weigand, 2017) ; and (8) Satisfied, loyal, and hardworking employees have a positive effect on the net profit of a bank (Budhathoki and Rai, 2018). Finally, increased profits facilitated by sustainability may also be mutually reinforcing, as banks that gain more profit have the resources to amplify the public good that they achieve with their externalities.

Sustainability may therefore both directly and indirectly increase the number of bank customers. As we found during our literature review that some studies argue that consumer trust is pivotal in the relation between sustainability and financial performance, we therefore argue that the effect of sustainable business models on a bank can be reflected by its number of customers. As such, this study will focus on customer market shares among the retail banks. By implication, this means that within this research context, the concepts of revenue and profit are represented by the number of customers.

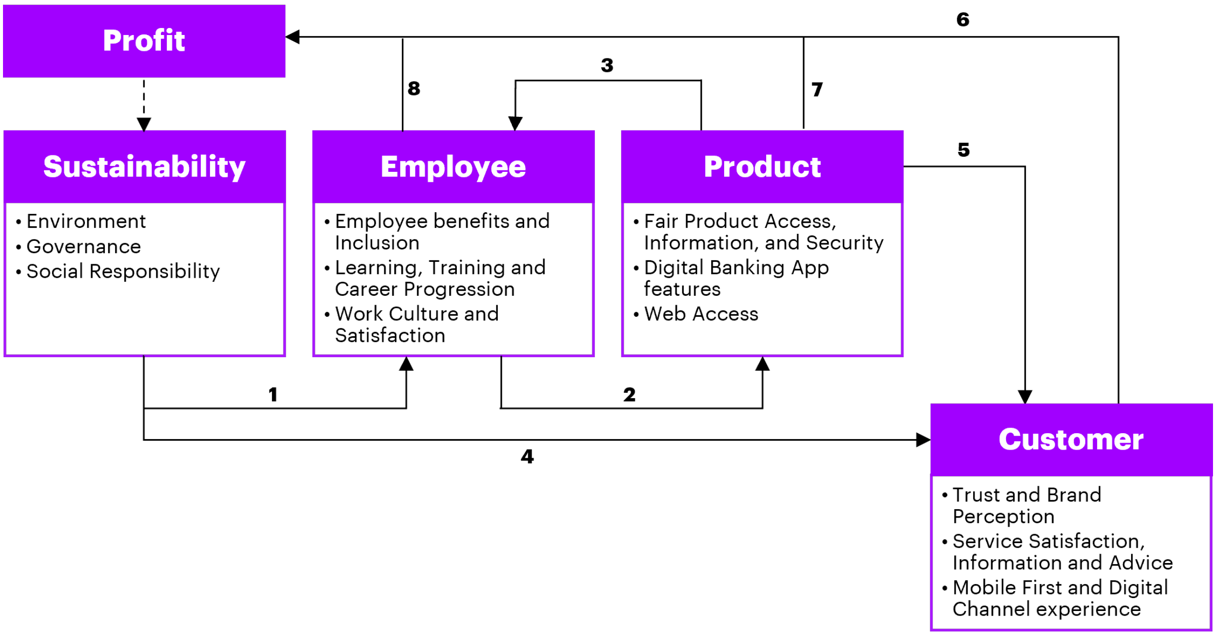

FIGURE 1.2: Proposed underlying mechanism of how sustainability leads to profit based on the four pillars from the Accenture Purpose-Driven Banking (PDB) Index (sustainability, employees, product, customers), each with three sub-pillars. Numbers indicate previously proven relations between the pillars.

Geographical limitations due to geographically determined consumer choice of bank behavior

As we focussed on the number of customers, we had to consider the observation that consumer preferences to sustainable banking are geographically different (Accenture, 2020). Consumer bank accounts are also geographically limited, as consumers have most of their bank accounts in the country they officially inhabit due to regulations that largely prevent opening foreign retail banking accounts. Advantageously, this makes it safe to assume that consumer preferences per country relate to the observations in the country's retail banking industry.

This study will therefore scope to the dynamics of the UK retail banking market. Studying the UK market has as advantage that all documentation is available in English and that it is the financial capital of Europe with many competitors and thus interesting dynamics in the system. In fact, the UK banking industry is also falling behind the rest of Europe regarding implementing sustainable banking and is therefore in particular need for insights on the system (Accenture, 2020). We furthermore note that corporate consumers, and, by implication, corporate banking is by default outside the scope of this research.

1.5.2 Main research question and thesis objectives

This study aims to address the lack of understanding in customer market share dynamics that emerge through the collective effect of banks' strategic decisions regarding the adoption of sustainable business models. To this end, we will use a simulation model. As such, the main research question is as follows:

What is the effect in the customer market share of UK retail banks when they adopt sustainable business models given their competitive environment?

The objectives of the research are two-fold: (i) exploring the range of dynamics in the customer market shares and their implications for the retail banking system to advise regulators, and (ii) advising bank managers on their strategic decisions regarding the adoption of a sustainable business plan given all other possible corporate strategy combinations that could be employed by their competition. The combination of these two approaches is unique and will facilitate robust model-based decision-making by regulators and bank managers. It must be noted, however, that the underlying ultimate objective of the modeling activity is an explanatory insight into the collective behavior of the banks, not numbers on customer market shares, as modeling is a means to an end rather than a goal in itself (Van Dam et al., 2012).

1.6 Research approach

We note that while modeling is a necessary step to gaining insights into the market share dynamics of UK retail banks, it is also a difficult task due to various reasons. Besides the question 'if' a bank should adopt a sustainable business model, there are temporal differences ('when') in their transition if they decide to do so (Lymbersky, 2008). The competitive position of a retail bank is thus determined by an ensemble of different choices, which is, in turn, made even more dynamic and uncertain by the decisions of competitors (Lymbersky, 2008; Skinner, 2021; Wright, 2002). Moreover, the process is also governed by external triggers from e.g., regulations and new entrants. The UK retail banking industry is thus a complex, open, uncertain, and dynamic multi-actor system in which strategic decisions are wicked problems that cannot be made risk-free (Rittel and Webber, 1974; Seyfang and Gilbert-Squires, 2019). As a consequence, there are many plausible future states of the system that can only be explored by a quantitative simulation approach of banks' interactions (Heckbert et al., 2010; Kwakkel and Pruyt, 2013).

1.6.1 Sub-questions

To facilitate answering the main research question using a modeling approach, we defined multiple sub-questions. In doing so, we realized that we also needed to answer an underlying methodological question of how market shares can be modeled while considering a (potentially) disruptive strategic innovation. This is because there are no existing modeling studies on the impact of a strategical innovation, and a suitable modeling method is thus yet to be proposed. As such, we defined two types of sub-questions: (i) the ones that deal with the complexity of the modeling activity in this study (indicated by an 'M'), and (ii) the ones that deal with theoretical implications of this study (indicated by a 'T').

- SQ.1 What modeling method is suitable to study the dynamics in customer market shares of UK retail banks when they are faced with a potentially disruptive strategic innovation, i.e., when they have to make decisions on the adoption of a sustainable business model (M)?
- SQ.2 What is the current state of the UK retail banking industry (T)?
- SQ.3 Which customer and bank behaviors influence the customer market shares in the UK retail banking system (T)?
- SQ.4 How can the effect of relevant customer and bank behaviors on the number of customers per bank be modeled (M)?
- SQ.5 What are the plausible future customer market share dynamics in the UK retail banking industry (T)?
- SQ.6 Are the model outcomes in line with the real world UK retail banking system it represents (M,T)?

1.7 Research outline

To answer the main research question, we adhered to a four-phase research plan, with each phase having multiple steps and answering multiple sub-questions (see Figure 1.3). We must note that while the steps are presented in series, we performed most steps in each phase in parallel and iteratively as ideas were refined and developed. The research phases, in turn, ensured that the sub-questions were answered in series, which was necessary as they built upon each other. As a result, we also intertwined the two storylines (i.e., theoretical and methodological) in this thesis.

In short, we first selected a suitable modeling method in Chapter 2. To this end, we reviewed existing market share model and evaluated if they can be applied to the research problem. Next, we collected data on the system under study, i.e., the UK retail banking industry, as developing a model required knowledge of both the system under study and modeling methods (Charan, 2020). That is, market dynamics had to be understood by the author of this thesis to ensure that they included all the variables that drive market share dynamics. As such, we demarcated the system in Chapter 3 by presenting a system inventory of the empirical context, relevant concepts, and relevant behaviors. We consequently leveraged these insights to design a conceptual model of relevant concepts that underlie customer market share dynamics in the UK retail banking industry.

Next, we transcribed the conceptual model into a simulation model through concept and model formalization. The former was performed in Chapter 4, in which we combined the selected modeling methods with the gained insights from the system inventory to formalize the concepts from the conceptual model into computer-understandable representations. The latter was performed in Chapter 5, in which we performed the actual software implementation and design of the simulation model.

Thereafter, we experimented with the simulation model in chapter 6. In Chapter 7, in turn, we verified and validated the simulation model. That is, we confirmed that the model represented a practical solution based on market realities to answer the main research question (i.e., that the model was fit-for-purpose).

Finally, we concluded this research in Chapter 8. To this end, we discussed the model outcomes, the limitations of the analysis, and potential future work. We furthermore interpreted the model both towards theoretical implications and practical implications in the form of policy recommendations.

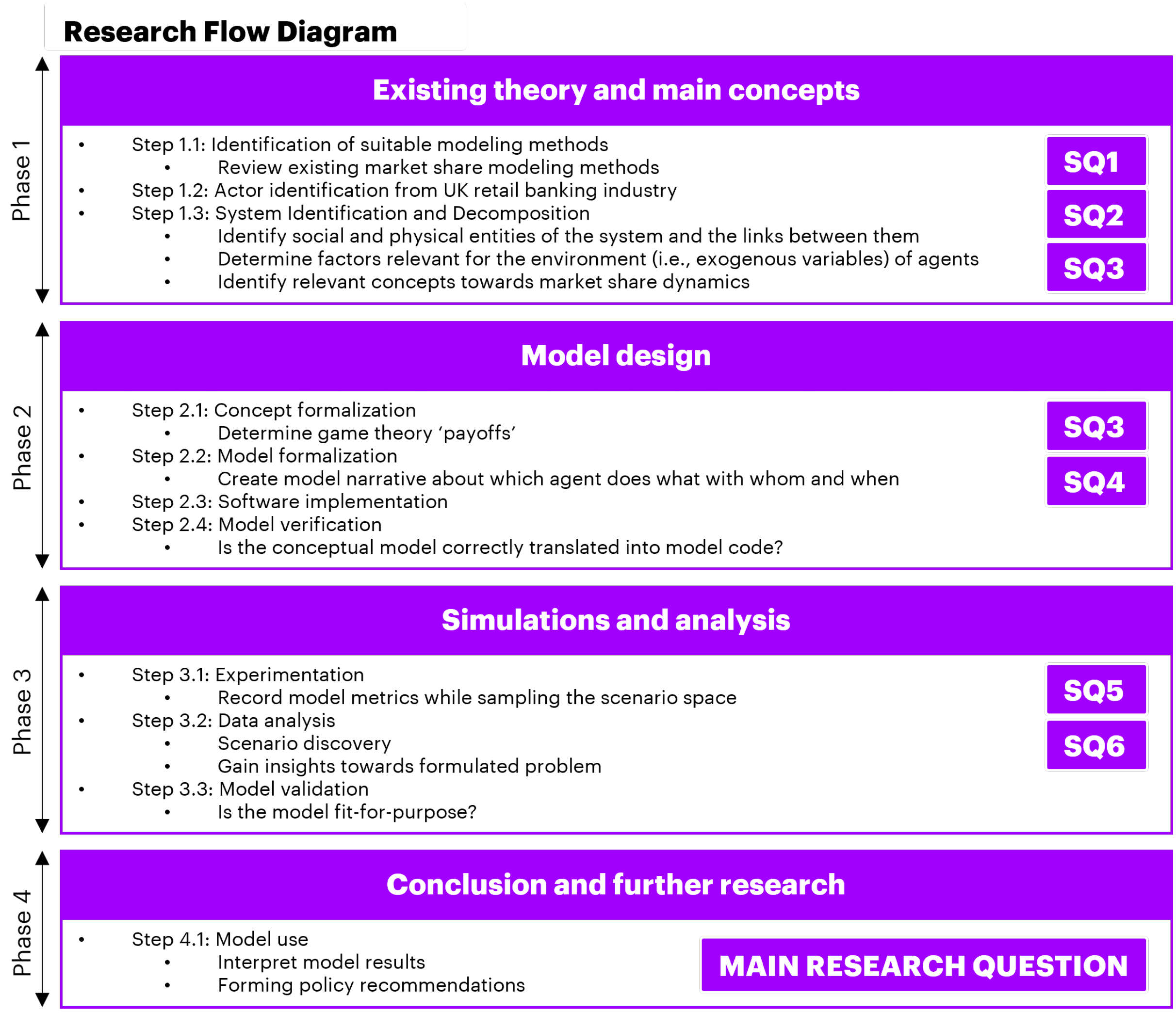

FIGURE 1.3: Research flow diagram indicating the four different research phases and their sub-steps, as well as the sub-questions that every research phase addresses.

Chapter 2

Research Methodology

In this chapter, we identify a suitable modeling method that allows the quantitative simulation of banks' interactions in order to gain the insights needed for answering the main research question (Heckbert et al., 2010; Kwakkel and Pruyt, 2013). Based on characteristics of the UK retail banking industry, we started by defining requirements that the modeling method should meet in section 2.1. Next, in section 2.2, we present a literature review of the available market share modeling methods and compare them to the set model requirements. Finally, in section 2.3, we identify a suitable modeling method. This chapter thereby answers SQ1.

2.1 Requirements of market share models

According to Cooper (1993), there are three basic principles that underlie the specification of market-share models. They should be (i) fundamentally competitive, as one cannot know the effect of a strategical decision without accounting for the decisions of others, (ii) descriptive as well as predictive, as prediction of the future from the past shares is insufficient in explaining how sales are generated, and (iii) profit-oriented, as market-share analysis prompts us to ask how an organization's allocation of resources to aspects of the strategical mix produce bottom-line results. Market shares themselves are, in turn, characterized by the following logical consistency requirements: they are positive, and their sum should equal 1 (Charan, 2020; Krehbiel, 1987). The latter requirement is important as it allows the forecasting of not only the values of market share by themselves, but also various dynamic market share relations across different brands or companies (Terui, 2000).

For studying the effect in the customer market share of UK retail banks when they adopt sustainable business models, however, we argue that the simulation method is subject to additional requirements:

- R.1 Inherent to modeling the effect of a strategic innovation that has disruptive potential, is the lack of detailed data on the consumer behavior towards this innovation. As such, the modeling method should not be data-driven (e.g., depend on historical time-series data) but rather be compatible with a scarcity of data that give mere hints on the consumer behavior.
- R.2 From the sudden rise of digital challengers, we know that banks which seem insignificant in their market share (i.e., share <0.5%) can initiate significant market share dynamics. As such, the modeling method should be compatible with including many banks (15+).
- R.3 Multiple variables influence the consumer choice of bank behavior and thus the bank's competitive position, including exogenous market trends. These variables might interact synergistically, (mutually) destructive, or not at all (Charan, 2020). As such, their influences cannot be studied in isolation and the modeling method should allow the inclusion of multiple (endogenous or exogenous) variables.
- R.4 The strategical decision-making of banks may have competitive effects (i.e., consumer switching their bank account) and/or market-extensive effects (i.e., market growth). Both these factors should be considered (Cooper, 1993).
- R.5 Underlying the dynamics in customer market shares are bank managers subjected to decision-making ('when' to adopt sustainable banking) under uncertainty (decisions of competition). As such, the modeling method should allow for the exploration of the collective effect of these strategic decisions that influence their competitive position (Lyons et al., 2003). Also, as the decision has a time component, the modeling method should model future market shares over

time in response to the changing state of the system, i.e., to the changing competitive positions of banks.

The above requirements can be summarized into the following characteristics of the modeling method: (i) the method employs some evaluation scheme for the effect of sustainable banking implementation strategies on the number of retail bank customers, (ii) the method is compatible with a dynamic environment in which the endogenous decision-making of autonomous entities influences their competitive position, and (iii) the method can be subject to a quantitative exploratory simulation approach to account for multiple future states (Kwakkel and Pruyt, 2013; Sterman, 1994).

2.2 Review of existing market share modeling methods

To identify methods that could meet the model design requirements, we reviewed existing share models. These kinds of models are employed by many fields of research, including marketing (market-shares) (Cooper and Nakanishi, 1989), political economy (shares of political parties) (Elff, 2009), and environmental planning (shares of different types of land use) (Chakir et al., 2016; Chaudhuri and Clarke, 2013). The literature search was performed similar as described in section 1.4, but did not contain a historical limit. The terms and phrases used were "market share" AND "modeling".

2.2.1 Regression-based modeling methods

A review of Morais et al. (2016) on statistical modeling methods adapted for shares as dependent variables identified four types of models that satisfy the logical consistency requirements: (i) multinomial logit (MNL) models as widely used in discrete choice models of the econometric literature, (ii) market-share models from the marketing literature, and (iii) Dirichlet covariate models and (iv) compositional regression models from the statistical literature. Please refer to Morais et al. (2016) for a detailed report of the properties, the similarities, and the differences between these models originating in their assumptions made on the distribution of the data, their parametrization, and from their estimation methods.

Multinomial logit models from econometric literature

MNL models are widely used to model discrete choices of individuals using individual data and multinomial logistic regression. That is, they model the static probability that an individual i chooses an alternative j that maximizes their utility, in which this alternative j is part of a finite set of mutually exclusive and collectively exhaustive alternatives that are either polytomous, discrete, or qualitative in nature (Agrawal and Schorling, 1996). If data at the individual level is not available, the closely-related conditional logit models might be used, as they require only the numbers of individuals who have chosen each alternative instead of the individual choices. The prediction of shares by MNL models is, however, static. This property makes MNL not suitable to model the system under study, as R.5 dictates that the model should predict a time-series modeling output. In addition, MNL models are not directly compatible with exogenous market trends that according to R.3 should be taken into account when explaining market dynamics (Marasco et al., 2016).

Market share models from marketing literature

Market share models are based on the notion that marketing effort (e.g., price, advertising) generates "attraction" for a brand, which is comparable to the "utility" concept in discrete choice models. The marketing factors function as explanatory variables and are, in turn, based on market-level data. Attractivity of brand j is expressed in terms of the explanatory variables describing brand j. The market share of brand j, in turn, is defined as its relative attractivity compared to its competitors, i.e., compared to the sum of attractivities of all the brands of the market (Charan, 2020).

Two main market share models exist. One is similar to the MNL model discussed above, and the other one is called the Multiplicative Competitive Interaction model (MCI). The only difference between the models is their functional form of explanatory variables: the log-linearized MCI takes the log(X) as explanatory, whereas the log-linearized MNL-type takes directly the X. As such, their sales response curves are concave and S-shaped, respectively. That is, both model outputs are characterized by diminishing returns to scale at high levels of marketing effort. Market share models are, however, static in nature. That is, the market environment as characterized by model parameters remain fixed over time, which means that R.4 and R.5 are not met (Charan, 2020). In addition, the fixed shapes of the possible response curves (e.g., linear, concave, s-shaped, or convex) limits the prediction of dynamics that cannot be described by these curves.

Compositional modeling methods from Statistical literature

Compositional data concerns the relative information between the components (parts) within a sample, where the total counts of these components is not relevant or is not of interest. This type of data can be analyzed by either Dirichlet regression or using compositional data analysis (CODA) based on Log-Ratio analysis (Morais et al., 2016). The former is a particular probabilistic model, whereas the latter is some mathematical transform that scales the compositional data, after which it can be used in many statistical models. This difference originates in the underlying assumptions on the distributions. Regarding Dirichlet regression, this method can be used to explain a compositional dependent variable Y (assumed to be Dirichlet distributed) by classical (non-Dirichlet) covariates. That is, predict the ratio in which the sum total Y (demand/forecast/etc.) can be distributed among the components X. The Dirichlet distribution (and Dirichlet regression by extension), however, assumes that the compositional parts (the variables X) are independent (Ankam and Bouguila, 2019; Morais et al., 2018). As the relative probabilities to choose a specific bank may drastically change depending on the PCA providers that are available to the consumer, R.3 is not met and, in general, we argue that Dirichlet covariate models thus cannot be applied to the banking industry. Log-Ratio transformations, on the other hand, allow for covariance between the components, but do not allow for complete independence (Ankam and Bouguila, 2019).

General limitations of regression models

The body of literature that uses regression-based methods is vast, and many model variations have been designed to addresses the multifaceted nature of share predictions. This includes models that consider the interactions and interdependencies within marketing mix variables, lagged responses, competition, and simultaneous relations between factors that hamper the discovery of their individual influences (Charan, 2020; Morais et al., 2016).

All regression models, however, generally rely on the (time series) analysis of extensive market data (i.e., a set of explanatory variables) to estimate a response variable (i.e., shares). As such, all the regression models do not meet R.1, i.e., no dependence on detailed data. In addition, the parametrization of regression models can only be solved through computational estimation methods such as maximum likelihood or Ordinary Least Squares (OLS) on coordinates (Morais et al., 2016). The effectiveness and computational demand of these methods, in turn, depends heavily on the number of parameters that have to be estimated. Generally speaking, the number of parameters in regression models increases drastically with the number of brands that are included in the simulation (approx. 5 is the maximum), as well as if so-called cross-effects are taking into account. These cross-effects entail that the utility of a product is a function of its own attributes and the attributes of competing products (Krehbiel, 1987). This increase in parameters forms a serious limitation of regression models, as computational demands exceed practical applications. As such, R.2 is not being met.

2.2.2 Differential equations methods

An alternative approach to modeling market share dynamics entails the use of competition Lotka–Volterra models (LV) (Cerqueti et al., 2015; Chiang, 2012; Lotka, 1925; Michalakelis et al., 2012). In these approaches, market shares are forecasted by first-order nonlinear differential equations that represent products/service providers competing for a common source: the market potential. The approach is, however, limited as it needs up-front categorization of the competition roles (i.e., predation, commensalism, mutualism, neutralism, or pure competition). This implies that the bank's competitive position is static, and as such, that R.3 is not met. What is more, LV models assume that the economic factors affecting market shares' dynamics (e.g., competition roles) are constant over the time interval considered, thereby not fulfilling R.5. Marasco et al. (2016) attempted to overcome these limitations by designing a nonautonomous LV model in which part of the parameters in the differential equations were modeled dependent on time. As such, the model is claimed to render justice to the dynamic nature of competition by allowing firms to change their competitive behavior over time. The model thus seems capable of capturing many important aspects of market share dynamics, however, the changes in market shares are not modeled consequent to the endogenous and autonomous strategic decisions made by bank managers. Rather, they are predicted by the fit of a first, second, or third order equation on historical market share data. As such, R.1 and R.5 are not met.

2.2.3 Machine learning methods

These have been a few attempts to predict market shares using machine learning methods, in which historical data of several input variables is used to train a classifier. While machine learning tools are a promising tool as they were demonstrated to outperform methods based on multiple regression, log linear, multiple discriminant, and multinomial probit models, they disadvantageously suffer from interpretability problems and require large amounts of historical data (Agrawal and Schorling, 1996). As such, R.1 is not met.

2.2.4 Previous studies on market share modeling in the banking industry

We have identified two studies in which the market shares within the banking industry were modeled, although both these studies rely on one of the methods described above. First, Amasyali et al. (2014) modeled the historical market shares of commercial banks operating in Turkey using computational intelligence algorithms. Interestingly, whereas normally consumer-related variables are used as training variables of the machine learning methods, this study used 20 financial ratios. While the historical market shares were replicated with this approach, predictions on the future market shares were not made. Rather, using feature selection, it was determined which financial rations had the biggest predictive value towards the market shares in the historical situation. Similarly, the study of Chalikias et al. (2016) did not make predictions of future market shares, but rather was designed as a proof of principle. That is, they propose that the competition among the four largest Greek banks can be investigated using a structured model based on 4x4 differential equations system based on Lanchester's combat model. The effectiveness of this approach is not proven, as the proposed mathematical model's predictions were not compared with empirical observations in order to analyze its fitting and forecasting accuracy. In addition, the authors already note that such a model will be more effective in duopolistic or oligopolistic markets. Besides both studies thus being based on a modeling method that does not meet the set model requirements, there are no insights available on how the modeling of future market share dynamics in the banking industry should be approached.

2.3 Selecting suitable modeling methods

All reviewed existing market share models fall short in their ability to meet the set model requirements (see Table 2.1). Most importantly, their dependence on detailed data is fundamentally incompatible with modeling the uncertain impact of a potentially disruptive strategic innovation. Moreover, we like to point out that the existing market share model are "mathematical models", and not "simulation models" (Maria, 1997). Mathematical models are powerful as they result in general equations and mathematical expressions for the relationships among the variables and results. That is, they result in an explicit expression of the pattern of behavior (e.g., exponential) that aims to be a true representation of the system, but this representation is also static. Simulation models, on the other hand, can be used to explore combinations of variables that cannot be controlled in a real system. The latter is requires for this study, and as such, we set out to identify modeling and simulation techniques that have not yet been used for the purpose of market share modeling, but theoretically meet the model requirements.

TABLE 2.1: Overview of existing modeling methods and their violation of the set model requirements.

Modeling method		**Violated model requirements**
Regression models	Multinomial logit models	R.1, R.2, R.3, R.5
	Market share models	R.1, R.2, R.4, R.5
	Compositional models	R.1, R.2, R.3
Differential equations methods		R.1, R.5
Machine learning methods		R.1

2.3.1 Game theory

Game theory is a discipline that studies the decision-making, and, by implication, the strategic thinking of self-interested interactive entities (Farooqui and Niazi, 2016). It employs a framework for strategic interaction, in which players attempt to calculate some "best response" to all other possible strategy combinations that could be employed by their fellow players. This best response is some strategy or a mix of strategies that optimizes their payoff, i.e., some indicator of well-being (in this study the number of customers). For those unfamiliar with game theory, its methodology is best illustrated by the classic prisoners' dilemma (see Box 1).

As such, we identified game theory as a suitable evaluation scheme for the effect of sustainable banking implementation strategies on the number of retail bank customers. Evolutionary game theory in particular allows the study of players wanting to maximize their aggregate payoff of some number of plays of the game (Weibull, 1997). This would relate to the temporal component of the problem at hand: when to adopt a sustainable business model given the moves of fellow players? Advantageously, game theory does not rely on data to determine the effect in the payoff consequent to strategic decisions, but rather relies on a payoff function that conforms to the real-world. In addition, there is no theoretical limit on the number of players in the game. As such, game theory directly meets R.1, R.2, and R.4.

Box 1: Example of game theory: the prisoner's dilemma

The prisoner's dilemma describes the case in which two people are arrested. These people are separated during the questioning and are told that if they confess to the crime and if their partner also confesses, they will each receive one year in prison. If one of them confesses while their partner denies, then the one that confessed will receive three years in prison while their partner goes free. If both deny, then they will each get two years in prison.

Player 1 \ Player 2	Confess	Deny
Confess	1, 1	3, 0
Deny	0, 3	2, 2

TABLE 2.2: Payoff matrix for prisoner's dilemma. Number indicate the years in prison for player 1 and player 2.

These outcomes can be represented by a so-called payoff matrix, which is a visual representation of all the possible outcomes that can occur when two people or groups have to make a strategic decision (see Table 2.2). In this case, there are two players, two strategies (confess or deny), and three possible outcomes (both spend one year in prison, two years, or one goes free while the other spends three years). In order to determine the outcome of a game, one takes the row of the strategy chosen by player 1 and the column of the strategy chosen by player 2. In this resulting cell, the first number is the payoff player 1 receives, and the second number is the payoff of player two. So, if player 1 decides to confess and player 2 denies, the outcome will be 3, 0 because player 2 will go free.
To determine the best response strategy for each player, one can determine the aggregate outcome. This is the sum of the values per cell. For the prisoner's dilemma, these are 2, 3, or 4. As the arrested people want their total time in prison to be as low as possible, they will both chose the option that gives the aggregated outcome of 2, which is both confessing to the crime.

Standalone game theory fails to meet the set model requirements

Game theory, however, assumes that all players are completely rational and that they all play the same game by considering all involved players (Farooqui and Niazi, 2016). Game theory also takes a rather mathematical approach to the costs and benefits of decisions to calculate some kind of equilibrium or simple cyclic state as a result of every player employing their best response strategy. This approach falls short under more realistic banking industry settings such as new entrants, banks considering only part of the players when evaluating their decision (e.g., only direct competitors of similar size), and possible mergers and acquisitions. In addition, banks also continuously try to influence their competitive position over time, meaning that one cannot mathematically determine upfront what their best response strategy will be as the system changes. Standalone game theory is thus also a mathematical modeling method and that fails to capture the complex nature of the system under investigation, and as such fails to meet R.5.

Previous studies based on game theory that advise on the strategical decision-making of bank managers.

The value and limitations of standalone game theory regarding strategic advice in the banking industry are also demonstrated by previous studies. First, there are some studies regarding the strategic interactions of entities within the banking market, and consequently advise on the best course of action given the actions of others. None of these studies, however, address changes in market shares. Moreover, the studies that do exist usually abstract out their research problem by applying the (iterated) prisoner's dilemma. That is, the game consists of merely two players (entities), and each player has two possible moves (often a 'do' and 'do not' option). It includes studies on strategies for corporate customer and bank trust (Dahlstrom et al., 2014), banking crimes and the effectiveness of banking supervision (Abdullah, 2010), conditions for cooperation between investors and their companies to mitigate climate change risks (Kruitwagen et al., 2017), and competitive pricing of products, services, and interest rates (Dincer et al., 2014). The study of Khanizad and Montazer (2018) comes closer to considering multiple competitive players in the banking industry by using cooperative game theory to investigate the potential of coalition forming to reduce costs and simultaneously increase profits. The study, however, assumes there is only a one-time decision moment and does not consider market dynamics that influence the decision-making process.

One could also argue that adopting a sustainable business model is somewhat related to the decision on whether to enter a new market. This specific decision-making process has been studied in market entry games in which multiple players decide to either enter the market or not for multiple iterations (Rapoport, 1995). These games, however, assume that there is no feedback in between rounds of other players' moves and that the capacity of the market is different and unrelated in every round. None of the previous computational strategic studies is thereby capable of meeting the conditions for the system at hand, such as being able to observe other players' moves and make decisions in response to market developments.

2.3.2 Agent-based modeling

Agent-based modeling (ABM) offers a suitable framework to overcome the limitations of stand-alone game theory by allowing a dynamic environment in which the endogenous decision-making of autonomous entities influences their competitive position. That is, ABM constitutes a bottom-up simulation technique in which emerging system behavior can be observed from the micro-interactions of agents (de Andrade et al., 2010; Van Dam et al., 2012). This can be applied to banks becoming sustainable, as agent-based models can easily contain game-theoretic models as a basis for the behavior of agents. In fact, using concepts from game theory towards the latter tackles the biggest challenge to an effective ABM model, concerning how to accurately represent the actions of agents on the basis of rewards (de Andrade et al., 2010; Farooqui and Niazi, 2016). ABM goes beyond the mathematical limits of game theory by modeling agents as autonomous and heterogeneous entities with bounded rationality. That is, their rational decision-making is limited by factors such as the complexity of the problem requiring a decision (i.e., cognitive limitation) and the time available to make the decision. There can therefore be system-level rationality that is not accessible by the individual agent. The actions of the agents themselves are determined under the influence of their state and the state of the environment, thereby allowing for adaptive agent behavior (de Andrade et al., 2010). Advantageously, the ABM environment thus allows the incorporation of critical UK retail banking industry characteristics, such as new entrants and banks' that continuously influence their competitive position. ABM is therefore a suitable simulation method towards our second modeling requirement by including relevant design concepts such as emergence of behavior, sensing between entities, and stochastic effects of variables.

2.3.3 Exploratory modeling and analysis

Finally, we identified Exploratory Modeling and Analysis (EMA) as a computational research methodology equipped to account for multiple future states. It does so by systematically exploring the consequences of system uncertainties on a pre-designed simulation model (Kwakkel and Pruyt, 2013). These uncertainties may encompass factors such as the probability distribution of variables, the appropriate conceptual model, or the correct valuation of alternative outcomes according to different stakeholders (Lempert, 2003). EMA copes with such uncertainties by performing extensive computational experiments on a set of plausible models that are formed by varying assumptions and parameters (Agusdinata, 2008). In so doing, EMA can transcend "what if" questions and also answer questions such as *"under what conditions may a behavior occur?", and "what are the plausible future dynamics in a phenomenon?* (Kwakkel and Pruyt, 2013). The "what if" questions are generally answered by open exploration using systemic sampling of the uncertainty space, whereas the latter questions are answered by directed search through optimization algorithms (Kwakkel, 2017).

Exploring large ensembles of plausible futures makes EMA contrast with the traditional consolidative approach to modeling, which unifies knowledge into a single "best" model that represents the real-world system (Auping, 2018; Bankes, 1993). These kinds of models, however, become unreliable in the presence of barriers to experimental validation, uncertainties, and/or possible strong non-linearity, as is the case with sustainable banking (Van Der Pas et al., 2010).

2.3.4 Selected modeling technique

Sub-question one promoted us to investigate what modeling method is suitable to study the dynamics in customer market shares of UK retail banks when they are faced with a potentially disruptive strategic innovation, i.e., when they have to make decisions on the adoption of a sustainable business model. We argue that this modeling method should use the language of game theory (e.g., payoff function, players, strategies) in the context of agent-based modeling while being subject to exploratory modeling analysis due to various reasons (see Figure 2.1). First, this combination meets all the set model requirements, in which the methodologies function complementary to overcome each other's individual limitations. Specifically, ABM combined with game theory concepts allows ex-ante exploration of the consequences of strategic decisions in light of potentially disruptive strategic innovation. This is because this methodology explicitly recognizes that real-world systems comprise a multitude of autonomous but interconnected elements that respond to an open, complex, dynamic, and uncertain environment (Van Dam et al., 2012). As such, our research method can overcome the limitations of current strategy advice in the banking sector, which is mostly studied by reviews of business models, abstracting the problem into only a few interacting banks, or by using static, historical data-based analytical models that cannot capture the dynamics, randomness, or even chaos in a variable. Second, despite the potential of game theory concepts combined with EMA to provide researchers and bank managers with insights on strategic innovation dilemmas, to the best of our knowledge such an approach has not been adopted for such a purpose before. In fact, game theory and EMA seem to not have been combined before. Given the novelty of our approach, we thus note that this study is exploratory in nature, pioneering the study of the potentially disruptive effect of strategic innovations using computational simulation methods.

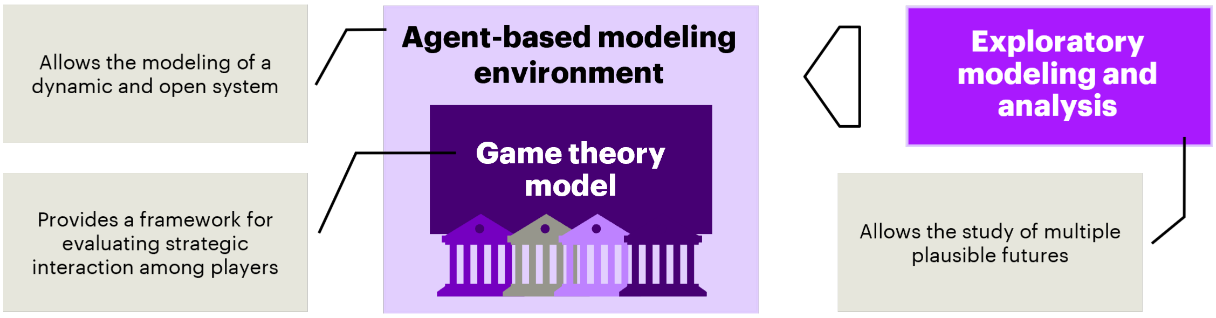

FIGURE 2.1: Combination of modeling techniques selected to design the model. The language of game theory is embedding in an agent-based modeling environment. The variables in this resulting simulation model are subject to exploratory modeling and analysis.

Chapter 3

System demarcation

In this chapter, we discuss relevant concepts and data on the UK retail banks and the system in which they operate (i.e., the UK retail banking industry) (Van Dam et al., 2012). While performing this system inventory, we demarcated the system boundary and thus the scope of the model. We started by determining the empirical context in section 3.1. With that, we aimed to get a definition of retail bank 'customers', a relevant time frame for simulating the system, and an actor identification. In section 3.2, we determined relevant concepts towards market share dynamics given the selected time frame. We specifically paid attention to identifying future trends in these concepts, which were crucial to the model that aimed to explore multiple plausible futures. In section 3.3, in turn, we identified the relevant consumer behaviors that underlie the relevant concepts. Finally, in section 3.4, we designed a conceptual model based on the findings from the system inventory. This chapter thereby answers SQ2 and SQ3.

It is important to note, however, that the information gathered during this system inventory contained many simplifications and assumptions, as the vast and complex system under study allowed interpretation only from a limited viewpoint. Desk research in the form of literature study and synthesis provided the main source of insights. We made sure to only select sources that used the UK as research context, thereby effectively preventing influences of system behavior from different countries/contexts. In addition, we performed semi-structured interviews to overcome gaps in data and increase our system understanding. Detailed reports of these interviews can be found in Appendix A.

3.1 Empirical context: The UK retail banking industry

As of 2020, the UK retail banking industry served c.97m personal current accounts (PCA) (i.e., transactional accounts), c.102m instant savings accounts, and over 7m fixed term deposit accounts. Overall, total retail deposits amounted to above £1.5 trillion (FCA, 2022c). Further products offered by retail banks included mortgages, personal loans, debit cards, and credit cards (Anandalakshmy et al., 2019).

3.1.1 Retail banking business models

A review of retail banking business models revealed that PCAs are generally at the heart of banks operations (FCA, 2022c). This is due to PCAs providing banks with large volumes at low costs, thereby granting the banks access to cheap and stable funding. This funding is consequently lend out to consumers and businesses in the form of mortgages, loans, credit cards, and overdrafts. In addition, 79% of customers take out savings accounts with their PCA provider, and the cross-selling of credit cards (48%), mortgage (22%), and other products has also been reported (FCA, 2021, 2022c). This cross-selling advantageously also has non-tangible benefits, such as increased brand loyalty and higher satisfaction amongst consumers (FCA, 2022c). With the pivotal role of PCAs in the retail banking industry, this study chose to define 'customers' of retail banks by the number of PCA customers. The PCA market was therefore leading for the remainder of this system inventory.

3.1.2 Influential regulatory shifts

Historical changes to retail banking business models have mostly come in response to regulatory shifts (McKinsey, 2019). These regulatory shifts, in turn, have often been introduced to mitigate or manage the adverse consequences of some debated matter within the retail banking industry. Some historical controversies include unethical profit maximization for shareholders in the '80s (Primeaux and Stieber, 1994), the anonymizing introduction of remote transactions (i.e., "FinTech") in the '90s (Cuesta et al., 2015), the 2008 financial crisis in which the then-largest UK banks were bailed out using public funds (UK

Parliament, 2018; Van der Cruijsen et al., 2016), and recent scandals such as the mis-selling of payment protection insurance (PPI) and the manipulation of the London InterBank Offered Rate (LIBOR) (Ashton and Hudson, 2013; PCBS, 2013). The latest matter of debate concerns the lack of sustainable actions in the UK retail banking sector, demonstrated by the fact that 90% of the 2018 ESG ratings of financial institutions were substandard (Järvinen, 2014; Laidlaw, 2018). This lack of sustainability is amongst others a consequence of how banks choose to finance other industries, including the fossil fuel industry (Bernardelli et al., 2022; Kirsch et al., 2021).

Promoting competition after the 2008 crisis

The crisis of 2008 incentivized the UK government to introduce regulations that protect consumers as well as make banks more resilient in the case of a crisis (Prorokowski, 2011). The Banking Reform Act, for instance, protects taxpayers when the banking industry fails, forces banks to separate their retail and investment activities, and imposes higher standards of conduct with the possibility of banks being sanctioned if they do not comply (DBIS, 2013, 2015). The UK government furthermore focused on fostering greater competition in the retail banking industry to *"make the financial system more responsive to consumers"* (DBIS, 2015). To lower the hassle of switching banks, for instance, they introduced a 7-day Current Account Switching Service (CASS) in September 2013 (Payments Authority, 2014-2021). In addition, competition through new entrants was promoted as the Prudential Regulation Authority (PRA) increased the facilitation of bank licensing applications and the Financial Conduct Authority (FCA) lowered capital and liquidity requirements (FCA and PRA, 2014). Promoting competition was followed up by a retail banking market investigation from CMA (2016) that identified market features with an adverse effect on competition. The study presented a package of remedies designed to address these problems, either executed by the Competition & Markets Authority (CMA) themselves or others, which are being monitored and implemented till date.

Commitment to increasing sustainable banking practices

With the ongoing climate change debate, it was also a matter of time before the UK launched its Green Finance Strategy in July 2019 (HM Treasury and BEIS, 2019). This strategy is part of the country's commitment to net-zero greenhouse gas emissions by 2050 (BEIS, 2019). Specifically, achieving net-zero requires a significant shift of investment into sustainable projects and green technology, and the Green Finance Strategy intents to do so in three separate phases (HM Treasury, 2021). The first phase needs to ensure that the information exists to enable every financial decision to factor in climate change and the environment. New economy-wide Sustainability Disclosure Requirements will be introduced to this end, which should be finished by 2026. The second phase, which currently lacks specification, must ensure that this information is mainstreamed into business and financial decisions. In turn, the third phase must ensure that financial flows across the economy shift to align with a net-zero and nature-positive economy. Given that sustainability disclosures will be obligated by 2026, we expect bank managers to actively consider adopting a sustainable business model in the coming years. As such, we deem a simulation timeframe of 7 years suitable. This entails the period of Q1 2022 up and including to Q4 2027. The one year added after the deadline accounts for an implementation period of becoming sustainable by 2026 at the latest.

It must also be noted, however, that the topic of sustainable banking had previously received attention from others. Academia, for instance, contested the governments' former attitude that competition would also inherently address sustainability by arguing that sustainable banking transitions were prevented by locked-in existing systems (Seyfang and Gilbert-Squires, 2019). In addition, multiple UK campaign groups such as Fossil Free UK, Move Your Money (MYM), and Global Justice have worked for years to make consumers aware of the unethical behavior of banks. For instance, MYM tries to motivate consumers to switch their bank provider by ranking banks on an ethical scorecard including factors such as transparency, climate change, and tax avoidance (Ethical Consumer, 2020).

3.1.3 Providers in the PCA market

Based on Ipsos (2022), who independently report on the 17 largest PCA providers in Great Britain and the 10 largest PCA providers in Northern Ireland as part of a regulatory requirement, we have synthesized a list of the 20 largest PCA providers in the UK by taking all unique banks mentioned in the report (see Table 3.1).

The PCA market is historically dominated by a few banking groups

It is generally reported that four big banking groups dominate the market: HSBC (includes First Direct and Marks & Spencer Bank), Barclays, Lloyds Banking Group (includes Lloyds Bank, Bank of Scotland, Halifax, and HBOS), and NatWest Group (includes NatWest, RBS, and Ulster Bank). Unlike some other major economies, the UK does thereby not have a significant major collection of independent local banks. This is the consequence of significant consolidation in the last 20 years (UK Finance, 2019). The 2008 crisis in particular led to nationalization by the UK Government of significant players like Northern Rock and Bradford & Bingley (now owned by Virgin Money), and to the acquisition of HBOS into the Lloyds Banking Group. In 2014, five banks controlled 85% of the PCA market, and all five were recognized household names over 150 years old. By 2018, fifteen of the banks and building societies which existed in 2000 were absorbed into six major groups: Lloyds banking group, Barclays, NatWest, HSBC, Nationwide, and Santander (the "main high street brands") (UK Finance, 2019). The market concentration in 2018 became as follows: the CR1 ratio was c.27% (i.e., the market share of the largest provider), the CR4 ratio was c.75% (i.e., the market share of the four-largest providers), and the Herfindahl-Hirschman Index (HHI) was c.1400, indicating that the UK PCA market was moderately concentrated (SMF, 2018). It was also concluded that despite new entrants, the market concentration had changed little since the separation of Lloyds and TSB in 2013.

Quantifying current PCA market shares is difficult by a lack of disclosure on relevant statistics

Obtaining detailed insights into the (historical) market shares was, however, close to impossible as most banks do not report the number of PCAs they serve (Expert 1). In addition, the numbers that were reported often included the results of all subsidiaries, allowing only a bird-eye view of the data without details at the individual brand level. As such, we have used literature synthesis and expert advice to estimate the current PCA market shares among the 20 most important players (see Table 3.1). These estimations are reported on extensively in Appendix section B.1. To get more feeling of the size of the retail banks, we also obtained their market share by Total Assets (2020) measured among all domestic banks (including investment banks, corporate banks, etc.) using the overview of TheBanks.eu (2020) (see Table 3.1). Comparing the different market share statistics demonstrated that some banks have retail banking not as their main business. Barclays, for instance, overwhelmingly leads in market share by total assets but does not for PCA market share, which can be explained by their main focus being on corporate- and investment banking.

TABLE 3.1: The 20 largest PCA providers in the UK and their relevant statistics. The estimations of PCA market shares are reported on in Appendix section B.1, the total assets market shares are obtained from TheBanks.eu (2020), and bank category indicates the type of bank as categorized by the authors of this study. Note that all subsidiaries of the four big banking groups have been included in the 'big 4' banks.

bank	Founded	Market share by # PCA accounts (estimated)	Market share by total assets (2020)	Bank category	Notes
AIB Group (UK) p.l.c.	1966	0.6%	0.12%	Mid-tier bank	Includes the First Trust Bank and Allied Irish Bank (GB).
Bank Of Ireland	1783	1.1%	N.A.	Mid-tier bank	
Bank of Scotland	1695	7%	3.13%	Big 4	
Barclays	1690	14%	10.50%	Big 4	
Co-operative	1872	1.4%	0.25%	Mid-tier bank	Includes the Smile.
Danske	1824	0.8%	N.A.	Mid-tier bank	
First Direct	1989	1%	N.A.	Big 4	
Halifax	1853	3%	N.A.	Big 4	

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bank	Founded	Market share by # PCA accounts (2020)	Market share by total assets (2020)	Category	Notes
HSBC	1865	10%	6.75%	Big 4	
Lloyds Bank	2009	13%	4.41%	Big 4	
Metro Bank	2010	1.1%	0.22%	Mid-tier bank	
Monzo Bank Limited	2015	5%	0.02%	Digital challenger	
Nationwide	1846	10%	N.A.	Scale challenger	Nationwide is a building society, meaning that it is owned by its members as a mutual organization. Setting policies and appointing directors is done on a one-member, one-vote basis.
NatWest	1968	8%	3.77%	Big 4	
RBS	1727	4%	0.98%	Big 4	Includes Adam & Company, Coutts and Isle of Man.
Santander	2010	11%	2.90%	Scale challenger	
Starling Bank Ltd	2014	2%	0.01%	Digital challenger	
TSB	1810	4%	0.42%	Scale challenger	
Ulster Bank	1836	1%	0.12%	Big 4	
Virgin Money	1995	2%	0.89%	Scale challenger	Clydesdale merged with Virgin Money in 2020 and rebranded to Virgin money
Low Volume Providers	Not applicable	N.A.	N.A.	Not applicable	Includes Arbuthnot Latham, C Hoare & Co, Coventry BS, Cumberland BS, Habib Bank Zurich plc, Hampden & Co, Investec, Reliance Bank, Spectrum Financial Group, Think Money Ltd, Unity Trust & Weatherbys Bank switches.

The historically strong position of the large PCA providers is weakening

A more recent investigation by the FCA (2022a) found that the historically strong position of the large PCA providers is starting to change as of 2018 (Figure 3.1). This fragmentation is unprecedented in the PCA market as an overwhelming amount of barriers to entry, including licensure laws, capital requirements, access to financing, regulatory compliance, and security concerns, have historically protected established providers (Cetorelli and Strahan, 2006; Rhoades, 1997). Indeed, when Metro Bank opened in 2010, it was the first bank to open in over 100 years.

The current dynamics in the market shares can be explained by increased competition - as facilitated by the government - with the longstanding consolidation of c.17-19 PCA providers now reaching 28 providers (FCA, 2022b). *"The role of the PCA as a fundamental driver of the full-service retail banking business model helps to explain why many banks, and some building societies, have sought to grow PCA market share and others have sought to enter the market"* (FCA, 2022c). It is, however, in the nature of these new competitors relative to the established players that we find full explanations of why they are currently gaining market share. To this end, we have categorized the PCA providers into different types of banks being big 4 banks, scale challengers, mid-tier, and digital challengers (see Table 3.1). We elaborate on each of these bank categories below.

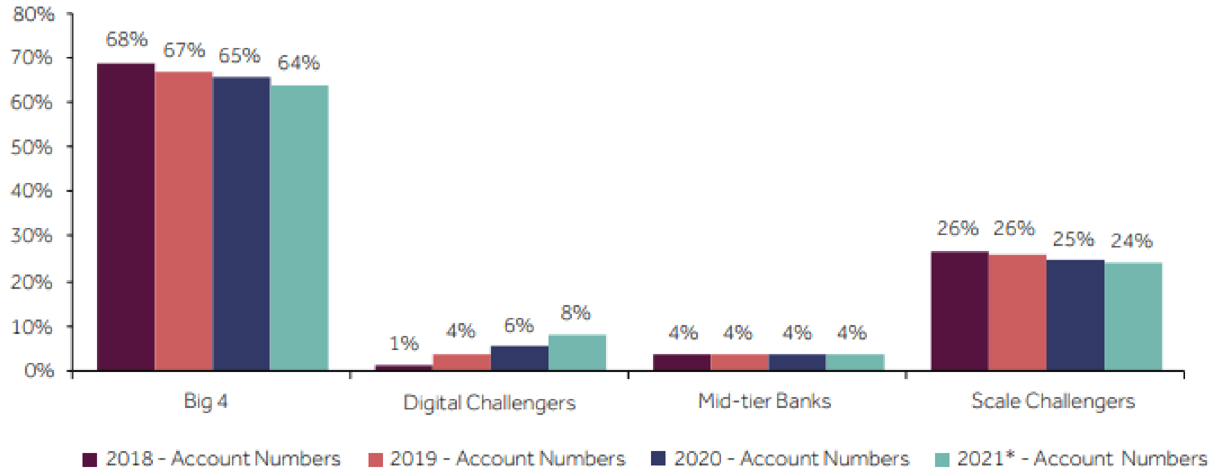

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FIGURE 3.1: Share of personal current accounts by account numbers. Figure obtained from FCA (2022a). Their sample includes 4 big banks (LBG, Barclays, HSBC, and NatWest), 3 scale challengers (Santander, Nationwide, Virgin Money UK, and TSB - not specified which bank is excluded), 2 mid-tier firms (Co-op, Metro, Tesco and Sainsbury's - not specified which banks are excluded), and 2 digital challengers (Starling and Monzo).

Big 4 banks

Large / traditional / incumbent banks (including their subsidiaries) have several advantages relative to challengers such as a large and loyal customer base, brand reputation built over several generations, size of their branch network, personal service, and other economies of scale (CMA, 2016). In addition, large banks (including large scale challengers) gain advantage through the established banking model in which their profit depends, for example, on the amount of money they can both bring-in and lend out, and more assets thus yields an advantage (SMF, 2018). Traditional banks therefore tend to have the highest PCA contributions of around £104 per account (FCA, 2022a). Another advantage for large banks comes from their ability to collect more consumer data, which also is a significant driver of banking competition (SMF, 2018). All together, these factors have historically protected their market shares. On the other hand, traditional banks often have more complicated and ongoing costs for their services. Approval processes for opening a new account can also be lengthy.

Scale challengers

Scale challengers are quite similar to traditional banks in their processes and have only slightly lower PCA contribution per account than Big 4 banks (FCA, 2022a). The scale challengers are therefore sometimes grouped with the big 4 into the "Big Eight high street banks". The historically strong position of traditional banks and the low consumer engagement in the PCA market, however, have caused scale challengers to struggle with organically building PCA market share CMA (2016); FCA (2022c). Market share has instead mostly been gained through mergers and acquisitions, or by offering monetary incentives (such as sign-on bonuses or high interest rates). This latter strategy results in (i) higher costs for acquiring funds that can subsequently be loaned, and thus lower profit margins, and (ii) that mostly price-sensitive customers are attracted, which are in turn more likely to switch their provider in the future (FCA, 2022c). The observed decline in scale challenger's market share might be explained by the latter (see Figure 3.1).

Mid-tier banks

Mid-tier banks are again quite similar to traditional banks in their processes and have only slightly lower PCA contribution per account than Big 4 banks, but they tend to have a strong regional presence serving the needs of local and loyal customers (FCA, 2022a). As such, their personal relationships and regular in-person interactions are superior to large financial institutions. And while their regional presence makes mid-tiers often overlooked, they are essential to resilience in the retail banking industry as *"a strong mid-tier, with a large enough scale, could substitute for any loss in the future provision of finance during an economic downturn, helping to further support the economy and ensure the profitability of the overall* *banking system"* (UK Finance, 2019). The market share growth of mid-tiers is, however, restricted as they lack the resources to compete on a national scale with the large banks. This includes struggles with retaining highly specialized, full-time technical personnel, meaning that the digital competencies of mid-tiers are often substandard (Guidehouse, 2021).

Digital challengers

Digital challengers provide customer-centric, fully digital banking services and are the first in the UK retail banking history to rapidly grow market share. The latter is the result of winning customers through a combination of PCA switches facilitated by CASS, customers opening their first PCA, and customers opening an additional PCA alongside their main PCA (FCA, 2022a). Gaining these customers so quickly was possible due to the previous standard of banking experiences being so poor. According to FCA (2022c), *"they have benefited from increased consumer preference towards digital channels, have a lower cost-base due to a lack of branch networks and have more modern IT infrastructures, allowing them to be agile with product-rollouts. In addition, digital banks have topped consumer satisfaction ratings, which has allowed them to win customers organically."*. They target mostly relatively younger, digitally enabled consumers. With tech-savy teenagers growing up, they thereby have an organically growing consumer segment.

On the other hand, the PCA accounts at digital challengers tend to have lower balances than at larger banks (their 8% of PCA market share accounts for merely 1.2% of the total balances in the PCA market) (FCA, 2022c). There are two causes to this observation: (i) many of the PCA accounts are 'secondary' accounts which are used with less intensity, and (ii) the targeted younger customers are, on average, less affluent than customers of other banks, and as such might have lower deposits. The PCA accounts at digital challengers thereby tend to generate lower transaction revenues and overdraft income. Secondary banking relationships are also associated with lower rates of cross-selling products such as savings and credit cards (FCA, 2022c). All these factors make it hard for the digital challengers to operate profitable. We also note that digital banks are often interchangeably referred to as neobanks, however, the main difference is that neobanks cannot offer PCAs as they lack a banking license (FCA, 2022b; Mobile Transaction, 2019; N-iX, 2021). Neobanks were therefore outside the scope of this system inventory.

Future outlook on PCA providers

It is expected that the PCA market will be subject to additional new entrants, as there have been 26 new applications for a banking license between April 2019 and April 2021 (Bank of England, 2021). For instance, JP Morgan Chase - a leading global financial services firm - launched their digital-only bank in the UK in 2021. The FCA (2022c) and Expert 2 expect JP Morgan to be a potential competitor for both incumbents and digital challengers, as they can easily leverage their existing global brand and innovate using sophisticated algorithms. In addition, since the last review of the FCA (2022a) in 2018, the majority of the traditional banks have caught up with the main innovations offered by digital challengers such as opening accounts online, budgeting tools, and in-app payments, and are as such currently on a convergence path. Dynamics in market shares are thus capable of incentivizing retail banks to change their business model.

3.1.4 Current PCA providers with a sustainable business model

To get an idea of how sustainable the providers in the PCA market currently are and which providers already have a sustainable business model, we obtained ESG scores from the Arabesque database (see Table 3.2). These scores are a measure *"calibrated using the principle of financial materiality, and can be used to help compare companies on their ability to outperform on a risk-adjusted basis over the long run"* (Arabesque, 2020). While Arabesque is a widely recognized and trusted provider of ESG scores, it is limited in its dataset as it only reports on companies that are publicly traded (Expert 1). In an attempt to get a more complete dataset, we therefore also obtained ESG Risk Ratings from Sustainalytics (Sustainalytics, 2022). These ratings measure a company's exposure to industry-specific material ESG risks and how well a company is managing those risks, resulting in five categories of risk severity: score 0-10 negligible, 10-20 low, 20-30 medium, 30-40 high, 40+ severe. Unfortunately, both sources reported data for all subsidiaries of the same group together. So, for instance, there was data reported for the Lloyds Banking Group, which included input from the Lloyds Bank, Bank of Scotland, and Halifax, amongst others. Per the suggestion of Expert 1, we therefore assigned all banks within the same banking group the same sustainability scores.

The new entrants, i.e., the digital challengers, were also not included in either of the datasets, and Expert 1 said to assume that their ESG scores are relatively high. Specifically, for the environmental score, the score should be >70 given that the new entrants are digital-only challengers without a large environmental footprint from a branch network. For the governance score, Expert 1 expected a relatively high score, given that the new entrants aim to do banking "the better way". The society score may be the only one that is lower than average, given that charity work etc. will likely not be a priority for a growing company that is trying to become profitable. Hence, we assigned the new entrants a ESG score of 66.

Overall, we observed quite some differences among the sustainability of the banks. Some banks operated quite sustainable (such as Co-operative, Nationwide, and Monzo), whereas others did not (such as TSB and Barclays). In addition, when looking at the ESG scores per pillar, we observed that all banks, except the Metro Bank, scored the worst for 'Social'. As such, we expect there to be quite some bank managers that will have to make strategic decisions towards the adoption of a sustainable business plan.

Table 3.2: Statistics on how sustainable the UK retail banks are currently operating. ESG scores were obtained fromArabesque (2020) on 31/03/2022, and ESG risk were obtained from Sustainalytics (2022). A bank was categorized as sustainable if it was among the top-performing 20%.

Bank name	**E**	**S**	**G**	**ESG**	**ESG risk**	**Note**	**Sustainable? (y/n)**
AIB Group (UK) p.l.c.	82,74	50,27	60,88	59,99	14,5		
Bank Of Ireland	61,46	49,23	56,64	54,05	20,8		
Bank of Scotland	66,98	37,09	61,59	50,44	20,6	Lloyds Group	
Barclays	58,22	29,99	55,14	43,08	17,3		
Co-operative	N.A.	N.A.	N.A.	N.A.	9,2		yes
Danske	64,83	32,67	53,81	45,72	24,1		
First Direct	65,54	36,11	47,51	46,04	19,3	HSBC Group	
Halifax	66,98	37,09	61,59	50,44	20,6	Lloyds Group	
HSBC	65,54	36,11	47,51	46,04	19,3	HSBC Group	
Lloyds Bank	66,98	37,09	61,59	50,44	20,6	Lloyds Group	
Metro Bank	40,00	43,98	54,59	45,93	N.A.		
Monzo Bank Limited	N.A.	N.A.	N.A.	66	N.A.	new entrants	yes
Nationwide	N.A.	N.A.	N.A.	N.A.	13,0		yes
NatWest	66,66	38,97	56,1	49,94	17,0	NatWest Group	
RBS	66,66	38,97	56,1	49,94	17,0	NatWest Group	
Santander	79,14	59,01	63,76	64,72	21,8		
Starling Bank Ltd	N.A.	N.A.	N.A.	66	N.A.	new entrants	yes
TSB	54,13	44,68	55,73	49,73	36,8		
Ulster Bank	66,66	38,97	56,1	49,94	17,0	NatWest Group	
Virgin Money	53,04	43,82	60,11	50,28	25,7		

3.2 Relevant concepts: drivers of customer market share and their future developments

As we aimed to study PCA market share dynamics, we identified relevant concepts towards these dynamics given the selected time frame. Indeed, in line with our research subject, we found that maintaining or increasing market share is often a key topic for bank managers, as market share is one of the main determinants of profitability, means less effort to increase sales, and corresponds to a strong barrier to entry for other competitors (Buzzell et al., 1975). To increase customer market share, retail banks must retain their current customers as well as acquire new customers at a rate that is higher than the market growth (Rust and Zahorik, 1993). If there is no market growth, bank managers might still increase their market share by having consumers switch their PCA, advantageously also directly decreasing the market share of the competition as a side effect.

3.2.1 PCA market growth

Market growth is caused by customers that seek to open their first PCA and customers opening an additional PCA alongside their main PCA. It is important to consider, however, that there is only growth if there are more consumers opening new PCAs than consumers closing them.

Market growth has seen a sudden upswing as of 2018

The PCA market increased from c.87 million accounts in 2018 to c.100 million accounts in 2021 (i.e., an increase of 15%), which implies a 3-year compound annual growth rate (CAGR) of 4.75% (see Figure 3.2) (FCA, 2022a). The growth rate, however, decreased over the years, possibly hinting at an imminent stagnation in future growth. Underlying the market growth is a strong shift towards multi-banking, which entails having more than one PCA per capita. As of 2021, there are c.1.85 PCA per capita, up from c.1.65 in 2018 (see Figure 3.2) (FCA, 2022a). Interestingly, in the period before 2018 there was little growth (1.62 PCA per capita in 2015 vs. 1.65 PCA per capita in 2018) (GfK NOP, 2015).

We must also note, however, that the net growth discussed above underrepresents how many customers seek to open their first or an additional bank account, and are thus available for acquisition by banks. This is illustrated by the following: c.9 million consumers indicated to have opened their first or an additional PCA in the past year (Accenture, 2020). This growth, however, is not consistent with data from the FCA (2022a), indicating that there is also a significant number of PCAs that get closed each year. Unfortunately, as there was no data available on the closing of bank accounts, we could not account for this discrepancy. We therefore assumed that the net market growth represents the total number of consumers available for acquisition, besides consumers that seek to switch their PCA provider.

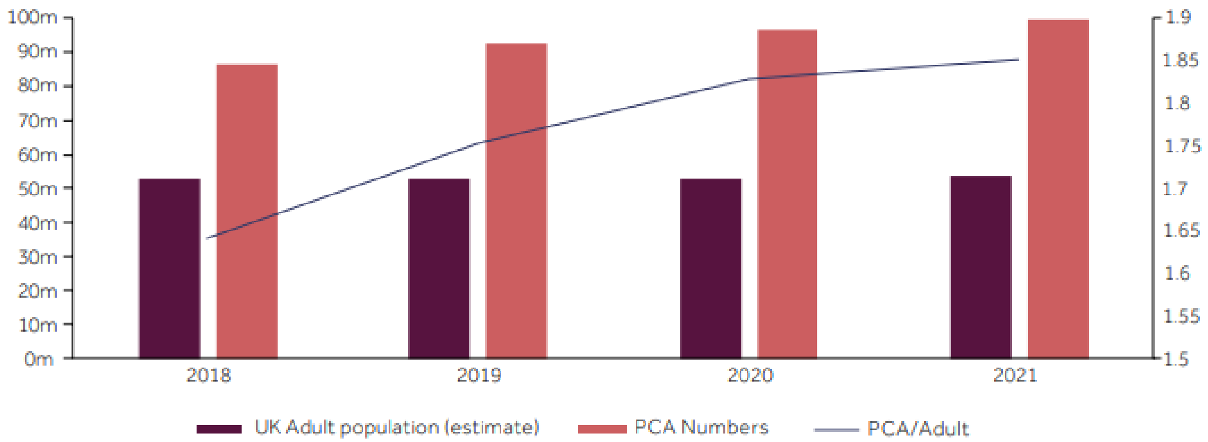

FIGURE 3.2: Personal current accounts per capita. Figure obtained from FCA (2022a). PCA/capita was calculated by dividing the total number of PCAs by the UK adult population.

Digital challengers have driven the observed market growth

Intriguingly, the somewhat sudden upswing in market growth corresponds to the timing of the new entrants. Indeed, the rise of multi-banking can be explained by easier onboarding and fewer hurdles in opening an account, driven by digital account openings introduced in 2018 by digital challengers (FCA, 2022a). Another important facilitator of multi-banking is the free-if-in-credit (FIIC) type of PCA, which was introduced in the mid-80s and allows consumers to trial PCAs with different providers without having to pay any monthly or annual fees (Bowman et al., 2014). The FCA (2022c) concluded that 75%

of consumers prefer these types of accounts, but they also are contested for having significant fees for overdrawn and making purchases in foreign currency. The latter may contribute as to why PCAs at digital challengers are less often used as the primary bank account.

Future market growth is expected to impede

Official governmental predictions on the PCA market growth have not been done. Some consulting and research corporates made growth projections, but these reports were not publicly available. According to Expert 2, *"precisely because some of these things are not predicted in the market commentary is because they are uncertain"*. And indeed, we recognize market growth as a deep uncertainty of the system. We therefore set out to find an uncertainty interval for the variable based on multiple market trends and historical data.

In line with the observation that PCA market growth is declining in magnitude, we expected the growth in the PCA market to impede. This expectation is supported by two arguments. First, we argue that there is an inherent difference between going from one PCA to two PCAs, and going from two PCAs to three or more PCAs. The first might be the consequence of convenience, separating accounts between fixed transactions and pleasure or having a shared account with a partner for household purposes, while the latter may encompass having accounts for detailed purposes or to stay below the £85,000 limit that is insured by the Financial Services Compensation Scheme (FSCS) if your provider goes bankrupt (FSCS, 2022) (Expert 2). Having more than two PCAs also increases complexity, which is something consumers are not eager about (FCA, 2022c). Second, population growth in the coming decade is small (3.2%) and mostly driven by immigrants, which we expected to not have multiple PCAs in the UK (Office of National Statistics, 2021).

We therefore predicted the PCA market growth to impede with a logarithmic curve and result in a PCA per capita of 2.0 by the end of our time frame, i.e., in seven years from now. Given that the growth in 2020-2021 was 0.03 PCA per capita, and we did not expect this to increase, the upper limit to the uncertainty interval was given by a linear projection of this rate. That is, 0.21 PCA per capita growth in seven years resulting in 2.1 PCA per capita by the end of our time frame. On the other hand, the lower limit of the uncertainty interval represented the possibility of barely any continued growth, resulting in 1.9 PCA per capita at the end of the simulation. We could also have argued that the lower limit should have been even lower, possibly representing consumers closing their second accounts and thereby leading to negative market growth, but we believe that the sunk costs of closing an account present a considerable barrier to doing so (Samuelson and Zeckhauser, 1988).

3.2.2 PCA switching volumes

PCA switching volumes have been a continuous matter of debate within the retail banking industry. Policymakers like to see increased switching volumes as, to some extent, switching volumes reinforce competition in the industry (CMA, 2016). On the other hand, inertia among switching has been more of a given than a surprise over the past years.

Historical CASS data

To gain insights into the historical PCA switching volumes, we obtained switching data from the Payments Authority (2014-2021), which is the authority responsible for the 7-day current account switching service (CASS). We captured the average change in switching volumes over time by calculating the Moving Average (MA) over three quarters with a centered interval from Q1 2016 to Q1 2022 (see Figure 3.3). We observed that the quarterly switching volumes were relatively stable between 220k - 240k in the pre-covid times (i.e., c.1 million a year), fell 2-3 fold during covid-peaks, and were stably increasing by c.13k in the post-covid time. We also observed that switching volumes generally peaked in the first quarter, possibly as a result of the often observed "new year, new monetary switching incentives" (Which?, 2022).

The drop during Covid may be explained by limited access to bank branches and the withdrawal of financial switching incentives by multiple providers (Ipsos, 2020). Whether the observed post-covid increase is a due to the switching levels returning to the pre-covid volumes or due to increased switching volumes as a result of different consumer behavior is currently unknown. Besides Covid, the year of 2020 was also characterized by the Brexit transition period. Possible influences of the Brexit therefore may also play a role in the deviating switching volumes. Nevertheless, we expected this influence to be small as the Brexit should not affect PCAs of the gross of the UK consumers and has been an ongoing topic, so we expect that consumers had anticipated its impacts and acted according spread over the years (European Banking Authority, 2020). We have also not found any reports on the influence of Brexit.

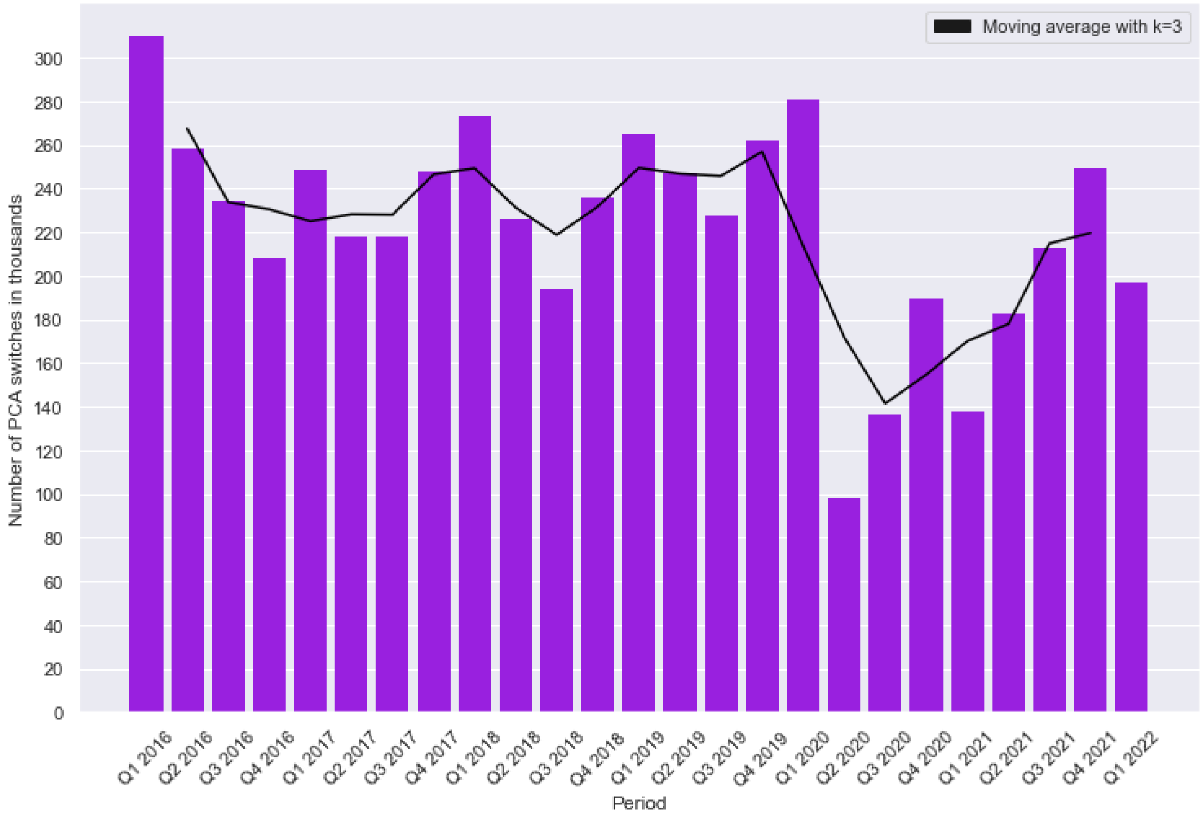

FIGURE 3.3: Quarterly number of PCA switches from Q1 2016 to Q1 2022. The moving average (black) was calculated with a centered interval of k=3. Data obtained from (Payments Authority, 2014-2021).

To get insights into the origin of the switches, we also visualized the CASS customer attrition and acquisition per PCA provider. Per category of PCA provider, we made the following observations: (i) the Big 4 banks and their subsidiaries have been losing customers since the entry of digital challengers, although Lloyds and NatWest have some quarters in which they are gaining customers, (ii) the scale challengers have also been losing customers since the entry of digital challengers, although Nationwide has significantly been gaining customers, (iii) the mid-tier banks have almost equal customer attrition and acquisition with much smaller magnitudes compared to the big 4 and the scale challengers, although the Co-operative has been losing customers, and (iv) the digital challengers have been gaining customers since their entry in the PCA market. These observations are in line with the observations made by the FCA (2022a) (see Figure 3.1). Interestingly, customer attrition seems to fluctuate less than customer acquisition. It would also have been insightful to have detailed data on the consumer choice of bank when leaving a specific bank X, but such a transfer matrix was unfortunately not available.

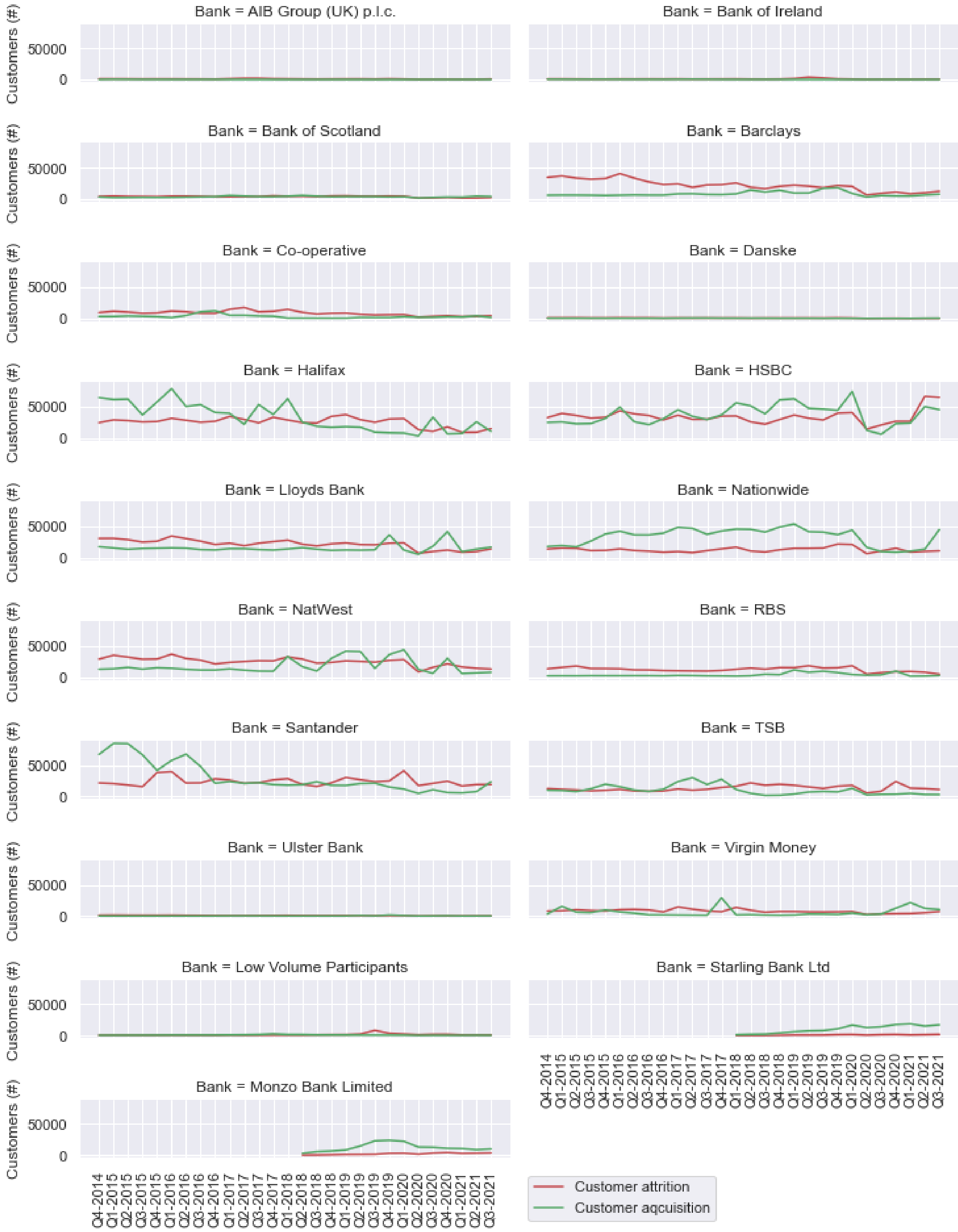

FIGURE 3.4: Historical consumer current account switching data displaying customer attrition (red) and customer acquisition (green) per UK retail bank between the period of Q4, 2014 and Q3, 2021. Note that we have displayed all banks under their name in 2022 (e.g., historical data of Clydesdale is represented under Virgin Money following their 2020 merger). The data was obtained from Payments Authority (2014-2021). The data of HSBC includes First Direct switches and data for Metro Bank was not available. The big 4 and their subsidiaries are Barclays, Halifax, HSBC, LLoyds Bank, NatWest, RBS, and Ulster Bank. The scale challengers are Nationwide, Santander, TSB, and Virgin Money. The mid-tier banks are AIB Group, Bank of Ireland, Bank of Scotland, Co-operative, and Danske. The digital challengers are Starling Bank and Monzo Bank.

CASS data is underrepresenting the actual historical switching volumes

While the CASS switching data is often cited by parties that comment on market developments, we must also make some critical notes on the reported numbers. Two years after the introduction of CASS, the service was evaluated by the FCA (2015). They found that the awareness of CASS as reported by third-parties was lower than as reported by the Payments Authority (41% vs. 70%), and also that confidence in the service was moderate (64%). As a result and against the governments' expectations, the performance of CASS as a facilitator of competition in the retail banking market was unsatisfying. In the first year that CASS had been in place, the Payments Council reported a 22% increase in annual switching volumes to c.1.2m switches. The volumes, however, already began to fall back in September 2014 and by January 2015 were just 16% higher than before the introduction of CASS (FCA, 2015). In response, a number of aspects of the CASS process that might still inhibit consumers from switching banks were identified and addressed, including marketing campaigns for awareness and forced compliance with the service for PCA providers, but a later report by the FCA and CMA (2018) found no significant improvements in the switching volumes. Any follow-up research after 2018 into the lacking performance of CASS has unfortunately not been performed, but Expert 2 confirms that the performance of CASS is still lacking.

Given all this, we argue that the switching volumes as observed from CASS data are underrepresenting reality. Nevertheless, CASS data advantageously reports on 'pure' switching volumes. That is, its quantity represents for 95%-97% PCA switches in which the old PCA is closed. We therefore suspected that more realistic historical (pre-covid) yearly switching volumes were the observed c.1 million a year / 41% reported consumer awareness = c.2.5 million switches per year. Expert 2, however, also emphasized the fact that there are quite some people that are not using CASS for switching. They expected that in reality, <10% of consumers switched their PCA per year, which could be translated in c.4m switches. The true historical switching volumes are thus ambiguous, but we guesstimated them to be c.3m based on the corrected CASS data and expert views.

Historical consumer surveys on PCA switching

Given the uncertainty in the historical switching volumes, we took an additional approach by evaluating consumer surveys contained questions such as "how long have you been with your current PCA provider"? and "how often do you switch bank account"? Unfortunately, all identified surveys reported their findings differently, which made direct comparison difficult (see Table 3.3). We therefore calculated the approximate yearly switches based on the baseline that there were 54 million UK adults in 2021 (Office of National Statistics, 2021). We furthermore assumed equal distributions on the indicated time intervals, that "more than once a year" meant twice a year, that "<3 years" meant one a year, and that "20+ years" and "10+ years" meant once in a lifetime (i.e., once per 80 years, with the assumption that 10+ years also included people that never switch). We observed significant differences in the resulting approximate yearly switching volumes, with the average being 8.7 million and a standard variation of 3.6 million (i.e., of 40%). Besides these inconsistencies between the survey outcomes, we also made some critical notes when evaluating the selected consumer studies (see Table 3.3). Amongst others, the number of consumers that reported to have switched in the past one or three years was consistently lower (c.30% to c.60%) than what we would expect based on the indicated time spend with their PCA provider.

But, most significantly, we observed a c.3-fold discrepancy between the switching volumes as reported by the consumer surveys and as reported by CASS. We attributed this discrepancy to insufficiently demarcated questions in the consumer surveys. The survey by Accenture (2020), for instance, is the only survey that asked the follow-up question of whether consumers opened a new PCA because they switched their previous PCA. 21% of adults indicated to have opened a new bank account in the past 12 months, and of this group, 21% did so because they switched their previous PCA. This comes down to 2.4 million yearly switches, which is in line with the guesstimated historical yearly switching volume of c.3m. Given that in the other surveys we could not reliably determine the number of 'pure' PCA switches, we decided to discard the consumer survey insights for validating our historical switching volume guesstimate.

TABLE 3.3: Overview of consumer surveys that report on historical switching volumes.

Source	Consumer response	Appr. yearly switching	Critical notes
Deposit solutions (2021)	The average time with a PCA provider is 11.5 years; and 7.5 years with a saving accounts provider	4.7 million	No higher level of detail is available.
FCA (2021)	<3 years: 9% 3 to 5 years: 7% 5 to 10 years: 16% 10+ years: 65% Do not know: 2%	7.4 million	6% of adults indicated to have switched their provider in the last three years, i.e., 3.2 million switches. This 6% deviates c.30% from the 9% that indicates to stay with their provider for <3 years.
Finder (2021)	61% of adults reports to have ever switched their bank accounts. Out of those switching: > once a year: 4.15% 1 to 2 years: 13.70% 3 to 5 years: 25.66% 6 to 9 years: 18.69% 10 to 19 years: 18.11% 20+ years: 19.68%	9.1 million	Survey seems to make no explicit distinction between PCAs, saving accounts, or any other bank account.
Accenture (2020)	Time spend with main bank: < a year: 5.4% 1 to 2 years: 8.1% 3 to 4 years: 12.5% 5 to 10 years: 20.6% 11 to 20 years: 22.4% 21 to 50 years: 27.8% 51+ years: 2.6%	13.4 million	21% of adults indicated to have opened a new bank account in the past 12 months, and of this group, 21% did so because they switched their previous PCA, i.e., 2.4 million switches and 8.9 million new PCAs. This accounts to 4.4% of consumers switching their bank account in the past year, which deviates c.60% with the reported 5.4% that stays with their bank < 1 year (which we assume to entail two switches per year).

Drivers of observed low switching volumes

Even though there is ambiguity in the historical switching volume, it is clear that the volume is small relative to the c.90m PCAs that existed in the pre-covid times. It can thus be concluded that in general, people do not like to switch banking relationships (FCA, 2021). According to Samuelson and Zeckhauser (1988), this is because the irrational mind interprets switching as risky behavior. The status quo therefore get disproportionately preferred, even when it makes rational and economic sense to change. This is due to a number of psychological biases including loss aversion (i.e., loss outweighs gains of the same magnitude), sunk costs, regret avoidance, or a reluctance to "cut your losses". In addition, the infrequent interaction with banking services makes the potential reward of switching banks markedly diminished on an experiential level (Forbes, 2019). Given the low switching volumes, both CASS and PCA providers seem to have been unsuccessful in helping people overcome some psychological barriers of switching.

In addition, the anatomy of customer-bank relationships adds to the switching inertia. Specifically, the lack of a natural 'break point', prompting customers to review their options and consider switching, fosters the inertia (SMF, 2018). In comparison, the insurance sector has contracts with specified end dates, and is consequently characterized by much higher switching volumes (e.g., 53% of consumers have switched their motor insurance vs. 6% their PCA in the past three years) (FCA, 2021).

Future consumer switching intentions

While switching inertia has been common, we identified multiple indicators that switching volumes might increase in the future. First, consumer surveys also tend to anticipate short-term future switching intentions. Two surveys found that c.17% of consumers are actively considering switching in the next year, with one of these being reported by the Payments Authority and therefore being assumed to be reasonable reliable (see Table 3.4). This switching intention is higher than the 8% reported in 2020, which, in turn, was already higher than it had been in the previous two years (Ipsos, 2020). And while this indeed might indicate an upswing in the switching volumes, we also are mindful of the so-called intention-behavior gap that describes the failure to translate intentions into action approximately one-half of the time (Sheeran and Webb, 2016). Yet, the consumer surveys hint that some consumer behavior change is imminent. Second, our time is characterized by a period of 'Generational Equipoise', with four large, similarly sized generational cohorts coexisting (Trajectory, 2016). With over half of Gen Z (1997 to 2012) having to turn 18, their influence on switching will approximately double at the end of the simulation time (see Table 3.4). Third, we hypothesize that the efforts to increase switching volumes might be dampened by the shift to multi-banking. That is, consumers that would have switched started to open additional bank accounts instead when the digital challengers entered the market. As such, there may be an increase in the switching volumes as the upswing in PCA market growth stagnates. All above factors have been confirmed by Expert 2, and all factors are expected to linearly increase switching volumes.

Furthermore, some parties suggested open banking as a facilitator to more switching as it allows the exchange of consumer data between banks, third-parties, and technical providers to serve customers with additional, personalized services (Company, 2017; Pay.uk, 2020). We, however, expected that the effect on PCA switching will only be minor, as a many FinTechs that operate in this manner are not licensed to provide PCAs. Expert 2 confirmed this line of thought. Finally, we figured that as switching becomes more common / easier / CASS gets more trusted, switches could also increase with some sort of reinforcing factor, i.e., with an exponential curve. Expert 2, however, does not expect this reinforcing effect given the consistent lacking performance of CASS over the past seven years.

Given all the above, we expected the following for the uncertainty interval. The lower limit is given by no changes in consumer behavior, meaning that at the end of the simulation there still are c.3m switches per year. The upper limit of the uncertainty interval is given by the prediction of Expert 2 that it would be surprising if yearly switching volumes increased to 15% of consumers, i.e., c.8m switches, at the end of the simulation time. This increase follows a linear curve. It must also be noted that according to Expert 2, there may be two types of events that cause the switching volumes to temporary increase. The first would be a trigger event, in which a sizeable bank falls or is subject to a scandal and (all) its customers need another PCA provider. The second is a shock event, in which new entrants like JP Morgen Chase become credible fast.

Source	Consumer response	Critical notes
FCA (2021)	22.9 million (44%) adults always or usually shopped around for financial products, 18% never does. 29% say they are more likely to shop around in the future because of Covid-19, 6% are less likely	Much of the impact will simply reinforce existing shopping around behaviors; If people did so before they will continue to do so. Relatively few will change their behavior, for instance, just 13% of those who never shopped around say they are more likely, while 11% of this same group says they are less likely.
Deposit solutions (2021)	17% of UK consumers are considering switching their PCA in the next 12 months.	
Payments Authority (2022)	One in six (16%) PCA holders are actively thinking about switching, while a further 12% are considering it.	Definition of "actively thinking" and "considering" are not given, as well as the timeline in which the PCA consumers expect to make this switch.
Finder (2021)	57% of gen Z adults switched their main account within two years of turning 18. By comparison, only 26% of millennials, 19% of generation X, and 16% of baby boomers did.	

Table 3.4: Overview of consumer surveys that report on the intention for switching

3.3 Consumer choice of bank behavior

The consumer choice of bank behavior is thus critical in driving PCA market growth and switching volumes. However, besides this overall tendency to seek an additional or alternative PCA provider, it is also important to understand which banks are more attractive to consumers. This consumer choice of bank behavior depends amongst others on age, gender, and geography, but most strongly on banking personality (Accenture, 2020). The latter comprises four categories: (i) Pragmatists are satisfied and trusting regarding banks, expect value for their money, are channel-agnostic, and self-assemble services from multiple providers (27% of UK consumers), (ii) Traditionalists value the human touch, avoid technology wherever possible, and are not satisfied nor trusting towards banks (27% of UK consumers) (iii) Pioneers are tech-savvy risk-takers hungry for innovation to optimize their money (17% of UK consumers), and (iv) Skeptics are tech-wary and generally dissatisfied and skeptic with their banks (29% of UK consumers) (Accenture, 2020). The number of Traditionalist declined by 9% relative to 2018 as Covid forced people into online banking, while the number of Skeptics increased with 6% and Pragmatists with 3%.

That banking behavior is rapidly changing is also reflected by the finding that as of 2021, 42% of customers (compared to 30% in 2020) have a preference for a non-traditional current account provider in the UK (GlobalData, 2021). In addition, consumers with any type of account at a neobank went up to 14.7% from 9.5% two years previous Accenture (2020). Generational differences, similarly as with the switching volumes, also play a role as younger consumers (17-38 years) are, for instance, almost twice as likely to consider ESG issues when making purchasing decisions than consumers over 38 years old (PwC, 2021). These findings again hint that sustainable banking is becoming an increasing important competitive differentiator.

3.3.1 Factors that influence the choice of bank

Before the rise of digital challengers, PCAs were perceived as simple products, with service differences between providers being perceived as inconsequential (Revealing Reality, 2017). Many consumers therefore felt little reason to switch if they were content with their provider. Digital challengers changed this view that "banks are all the same" by providing innovative consumer-centric, digital-first services. As such, if consumers are nowadays asked questions concerning the factors they deem important when choosing a bank, they tend to give diverse answers (see Table 3.5). Interestingly, we observed that a significant proportion of the indicated factors are not specific to any feature that the different categories of banks have used to distinguish themselves, such as digital, branch networks, or sustainability, but rather to rates and rewards, service, and personalization. Given that PCAs are no interest-bearing deposit accounts, it is interesting that this factor is so common. According to Expert 1, the factor most likely encompasses consumers' perception on the monetary rewards offered when opening a new account (avg. £30), which are significantly higher if the new account opening is the result of switching a previous provider (avg. £150).

Besides the monetary incentives that competitors use to influence their attractiveness to consumers, there are some exogenous drivers such as the increased pace of digitalization, the low-interest rate environment, and the covid pandemic that have altered the way in which the market functions. The Payments Authority (2022), for instance, noted that *"while consumer switching trends were typically influenced by the cash incentives offered by the providers, the latest data for Q4 2021 also shows that service related, non-financial reasons, were the most significant contributors to people favoring their new PCA once a switch had been completed"*. The ongoing low interest rates thus seem to open the door to more switching for 'soft' reasons by neutralizing the financial incentive (Deposit solutions, 2021).

On the other hand, the reasons for leaving a specific bank seem to be more concerned with just service factors, possibly also explaining why historical consumer attrition was observed to be more constant than customer acquisition (see Figure 3.4). According to Forbes (2019), consumers are naturally more motivated to switch *"when they are unhappy with their financial institution for any number of reasons, including negative customer experience, service shortfall, bank errors or mistakes, or repeated service failures"*. These observations are in line with findings in the Turkey banking industry: the intention to stay loyal to a PCA provider is influenced by satisfaction of multiple service-related criteria, which is to some degree under the control of the bank (Demir and Demir, 2019).

TABLE 3.5: Overview of consumer surveys that ask participants about factors that influence their choice of bank.

Source	Consumer response	Critical notes
GlobalData (2021)	Why consumers prefer non-traditional bank providers: better rates and rewards (27%), better overall security 15%, superior digital banking functionality 13%, better customer service 11%, more advanced digital budgeting tools 10%, recommended by friend/family 9%, align with my ESG values 8%, appealing brand image 8%.	
Accenture (2020)	Which factors are most important to you when dealing with banks and insurers? value for money 36%, fast resolution to any issues I may have 23%, Speedy and efficient service 28%, Recommendations of appropriate products/services 6%,Polite and knowledgeable staff 24%, Personalised services (e.g., offers, savings tips) 9%, Able to manage my account in the way I want 36%, Able to contact my bank/insurer when I want 22%, Ethical & sustainable business practices 12%, Competitive pricing 26%, Clear and transparent communications 22%, Broad range of flexible, high-quality products 14%, Attractive digital banking proposition (e.g., online/mobile banking) 11%, Attractive customer loyalty program 15%, and Appealing brand 6%	Respondents were allowed to indicate three answers. Some options seem to be quite similar
Payments Authority (2022)	Factors why consumers prefer their new PCA once a switch had been completed: better online banking facilities (51%), sophisticated mobile or app-based banking systems (41%), improved customer service (38%), Location of branches (24%), and preferable account fees or charges (23%).	
FCA (2022c)	The top reasons for switching to a digital challenger are their mobile banking offer (33%), because it was recommended by a family or friend (30%), or because of lower charges (15%). On the other hand, the top reasons for switching into a Big 4 provider is the location of their branch (34%), their branch's opening hours (23%), or cash incentives (16%).	
Raconteur (2019)	What influences your choice of bank: ease and convenience of service (47%), brand trust (45%), price/rate (43%), service resolution quality and timeliness (43%), and wide network coverage of ATMs (40%).	

3.4 Summary of system inventory

While researching the empirical context, we touched upon multiple drivers of change in the PCA market: the political and regulatory environment (e.g., increased competition and sustainability requirements), technology and innovation (e.g., digital-only banks), customer behavior and demand (e.g., multi-banking, sustainability, convenience), and macro-and socio-economic developments (e.g., low-interest rate, demography). They all hint that a new retail banking landscape is forming, in which further changes in customer market shares among the players could be imminent. As such, the answer to sub-question two - concerning the current state of the UK retail banking industry - is that the state is evolving with uncertain effects on the UK retail banking industry in the long run. Nevertheless, the current state of the system does seem to facilitate the rise of sustainable banking as a potentially disruptive strategic innovation (Giesen et al., 2010).

We furthermore found that as a result of the changing UK retail banking industry, both the direct drivers of market share dynamics - being consumers switching their PCAs and consumers opening a new (additional) PCA (i.e., PCA market growth) - are uncertain towards the future. The former is expected to increase after a decade of low switching volumes, whereas the latter is expected to impede after a few years of rapid growth consequent to the entry of digital challengers. The rise of digital challengers furthermore demonstrates that strategic disruptive innovation within the UK retail banking sector has the potential to benefit a broader set of consumers without having to switch providers, as digital competence is currently being commoditized. This observation confirms the belief of regulators that disruptive innovation in the form of sustainable banking has the potential to transform the retail banking industry into a sustainable operation within a decade. In addition, as digital competence is becoming less of a unique selling point, sustainability as a competitive differentiator is becoming more relevant than ever.

3.4.1 Conceptual model

The propensities to seek another PCA provider - whether through PCA switching or opening an additional account - are in part consumer specific, and in part influenced by banks as to how attractive they are (Demir and Demir, 2019). This implies that both the behavior of banks and of consumers should play a pivotal role in the simulation model. As such, the answer to sub-question three - concerning the consumer and bank behaviors that influence the consumer market shares in the UK retail banking industry - can be given by designing a conceptual model that represents the system under study. Specifically, the conceptual model describes key processes that the simulation model will encompass, including changes in market shares consequent to the consumer choice of bank behavior, and the decisions of bank managers in a competitive environment.

At every simulation time step, two serial processes influence the market shares(see Figure 3.5). First, the customer attrition per bank due to switching volumes is simulated. Second, this group of consumers and the additional number of consumers available for acquisition due to PCA market growth are redistributed among the banks, thereby representing their customer acquisition. The number of customers per bank, and, by implication, their market shares, can thus be studied over time. Note that both consumer attrition and acquisition will depend on the consumer choice of bank behavior, as well as the relative attractiveness of banks to consumers.

This latter attractiveness is something that banks actively try to influence during the simulation. Specifically, each round of receiving payoffs is followed by strategic decisions of banks as to 'if', and if so, 'when' they adopt a sustainable business plan (see Figure 3.5). This decision depends on the observations that a bank can make about the system and themself. For instance, a bank might have the strategy to wait and observe what the moves of competitors are before making a decision. Once the decision to adopt a sustainable business plan has been made, a bank can no longer make any decisions, as committing to the execution of sustainable banking takes time. Retail banks that are already classified as being sustainable at the start of the simulation are therefore latent players that will not make any decisions.

Please note that in this thesis, we thus only consider direct market players such as the banks and consumers. Further entities that influence the business environment such as regulatory agencies and infrastructure providers are out of scope. As such, the system under study can be regarded as a basic market system, although we distinguish ourselves from economist by regarding each bank as an autonomous and heterogeneous agent that responds to its environment.

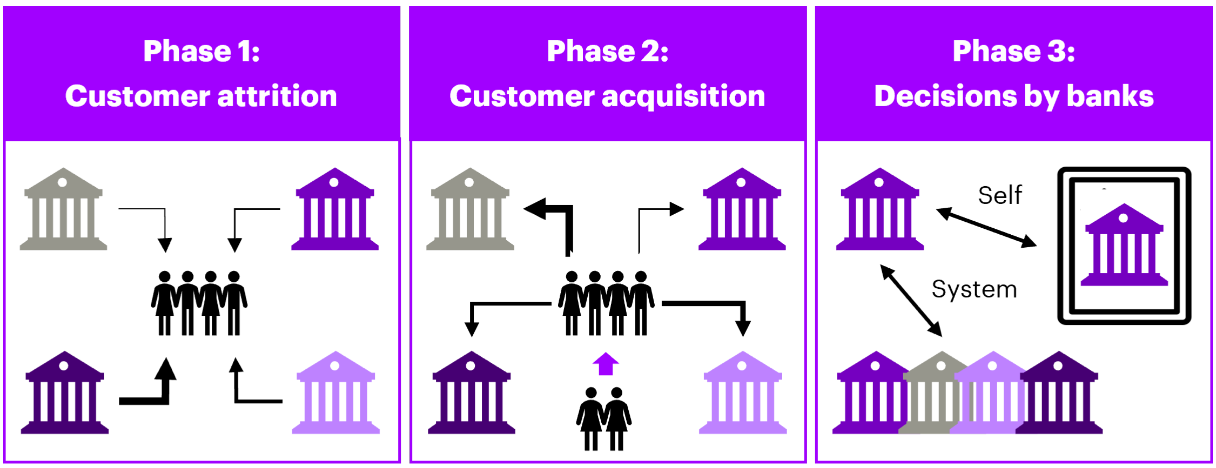

FIGURE 3.5: Conceptual model representing the system under study. In every simulation step, market share dynamics are modeled by banks' customer attrition and acquisition, and banks can consequently take the decision to adopt a sustainable business model. This decision can be made based on observation of the system and/or the self.

Chapter 4

Concept formalization

In this chapter, we formalize the states, relationships, behaviors, and interactions of the banks and their system as described in the conceptual model (Van Dam et al., 2012). That is, the (sometimes qualitative) concepts were transformed into both computer- and human-understandable representations by the use of e.g., numbers, strings, or Booleans. Towards this question of how certain concepts could be modeled, we adhered to the predicate from Auchincloss and Garcia (2015) that *"good models balance simplicity and adequate representation, incorporating enough key elements and processes and ignoring those that are not directly relevant"*.

The conceptual model implied that the attractiveness of banks should play a crucial role in the simulation model, as this attractiveness (i) can be influenced by the strategic decisions of banks managers in an attempt to influence their competitive position, and (ii) influences the consumer choice of bank, and, thereby, banks' customer attrition and acquisition. This is in line with the reasoning behind existing market share models, in which the market share of brand j is defined as its relative attractivity compared to its competitors, i.e., compared to the sum of attractivities of all the brands of the market (Charan, 2020; Marasco et al., 2016). We therefore first designed methods to model the attractiveness of banks in section 4.1, and consequently discuss the conceptualization of the strategic decisions of banks in section 4.2. Next, in section 4.3, we explain how we modeled the consumer choice of bank behavior in response to the attractiveness of banks. Based on the integration of methods from the previous sections, we present a payoff function that quantifies customer attrition and acquisition per bank in section 4.4. Finally, section 4.5 integrates all methods into a blueprint for a simulation model. This chapter thereby answers SQ4.

4.1 Quantifying the attractiveness of banks

To obtain quantities that were indicative of the attractiveness of banks, we grouped the reasons for choosing or leaving a specific bank - as identified in section 3.3 - into four categories:

1. Sustainability: sustainability aspects, brand trust, brand image;
2. Digital: digital banking portfolio, mobile services;
3. Rates and rewards: value for money, competitive pricing;
4. Service: speedy and efficient service, customer experience, polite staff, clear and transparent communication, location of branches.

As each of these categories represented a specific bank characteristic (e.g., their digital competence) that had advantageously been researched before, we quantified each so-called back feature using two proxies (see Table 3.2 (sustainability proxies) and 4.1 (digital, price, and service proxies) as well as Figure 4.7):

- Sustainability: ESG scores from the Arabesque database (Arabesque, 2020) and ESG risk ratings from (Sustainalytics, 2022). Expert 1 confirmed these to be suitable proxies for sustainability.
- Digital: Google Play Store App Ratings and a consumer survey asking how likely consumers were to recommend their provider's online and mobile banking services to friends and family (Ipsos, 2022).
- Price: Current offers of switching incentives (MoneySavingExpert, 2022) and a consumer survey asking how likely consumers were to recommend their provider's overdraft services to friends and family (Ipsos, 2022).

- Service: A survey asking consumers to rate their service Which? (2022) and a consumer survey asking how likely consumers were to recommend their PCA provider to friends and family Ipsos (2022).

Using two proxies per feature served a dual purpose of overcoming gaps in data, as well as attempting to get a measure for the bank features that most accurately represented reality. The latter required (i) to include at least one proxy per feature that represented the subjective responses of consumers (except for sustainability) as this was a more suitable measure of the attractiveness to a consumer than proxies that are objective in nature (e.g., the number of interruptions in digital service), and (ii) to overcome the bias in individual bank features by taking the average of multiple features. Specifically, the proxies for digital and service were strongly correlated (digital: Spearman Coefficient [1]0.76, p-value=7.1e-4; service: Spearman Coefficient 0.82, p-value=1.2e-4), but the correlations were weaker between lower values of the proxies (see Figure B.2 and B.4). The proxies for sustainability and price did not correlate (sustainability: Spearman Coefficient 0.05, p-value=8.5e-1; price: Spearman Coefficient 0.19, p-value=4.2e-1) (see Figure B.1 and B.3).

As such, we obtained the average of the proxies after they were made compatible by scaling each proxy to a unit interval between 0-1. In the end, we thereby represented each bank feature as an arbitrary number between 0-1 (see Figure 4.7). It must also be noted that the second sustainability proxy, ESG risk, was the only proxy with a lower score being indicative of a better performance. Hence, this proxy was first inverted after it was scaled to a unit interval, and consequently averaged with the other sustainability proxy.

TABLE 4.1: Used proxies for the digital, price, and service bank features

	Digital		**Price**		**Service**	
bank	**Google Play App Store rating**	**Online and digital banking service**	**Current switching incentives**	**Overdraft service**	**Consumer score**	**Overall service quality**
AIB Group (UK) p.l.c.	3,4	59%	0	38%	N.A.	44%
Bank Of Ireland	2,4	58%	0	53%	N.A.	53%
Bank of Scotland	4,1	77%	0	57%	64%	60%
Barclays	4,3	79%	150	67%	65%	64%
Co-operative	N.A.	60%	20	52%	70%	52%
Danske	3,6	75%	150	60%	N.A.	59%
First Direct	N.A.	81%	0	73%	82%	79%
Halifax	4,7	79%	0	59%	67%	62%
HSBC	3,6	73%	150	58%	57%	57%
Lloyds Bank	3,2	77%	125	65%	66%	62%
Metro Bank	4,8	78%	0	72%	77%	74%
Monzo Bank Limited	4,4	85%	5	66%	83%	80%
Nationwide	N.A.	79%	125	56%	75%	68%
NatWest	4,2	74%	0	46%	67%	57%
RBS	3,6	68%	0	49%	56%	48%
Santander	4,5	77%	0	58%	66%	56%
Starling Bank Ltd	4,6	86%	0	68%	85%	81%
TSB	4,1	62%	0	51%	59%	49%

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[1]Throughout this study, we consistently calculated Spearman correlations and not Pearson correlations, even when trends appeared linear. Whereas the Spearman correlation can safely handle our (sometimes ordinal) variables with skewed distributions and is insensitive to sometimes present extreme values, the Pearson correlation cannot and is inappropriate for our data (Mukaka, 2012).

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	Digital		Price		Service	
bank	**Google Play App Store rating**	**Online and digital banking service**	**Current switching incentives**	**Overdraft service**	**Consumer score**	**Overall service quality**
Ulster Bank	4,5	77%	20	58%	N.A.	58%
Virgin Money	N.A.	61%	20	52%	63%	49%

4.2 Modeling the strategic decisions of bank managers

Bank managers continuously make strategic decisions that aim to increase their attractiveness to consumers. This implied that the bank features could not be represented by static values in our simulation model. As such, we modeled their dynamics both in a endogenous and exogenous manner.

4.2.1 Endogenously modeled bank decisions

In this study, we specifically aimed to investigate the strategic decision of whether, and if so when, bank managers should adopt a sustainable business model. As such, this decision-making process had to be modeled endogenously.

Common strategies in business model innovation

Underlying the decision to change a business model is a certain strategy by a bank. In practice, however, banks rarely report on the implementation strategy that they have used. As such, we used a synthesis of classic literature on strategies for business innovation to identify sustainable banking implementation strategies that could be used to model the behavior of banks.

First, according to Porter (1980, 1985), there are two possible strategies to reach superior performance. This is either by offering no frills products at low prices or by offering differentiated products for which consumers are willing to pay a premium price. This rather neoclassic economic view ascribes competitive advantage thus to external characteristics rather than to banks' distinctive competencies and resource-based deployments.

Miles et al. (1978) contradict the idea that a bank should either focus on costs or differentiation. Instead, they argue that organizations are in constant dynamic interaction with their environment in an attempt to survive in a market. In doing so, they generally encounter three types of problems: (i) the entrepreneurial problem, (ii) the engineering / operational problem, and (iii) the administrative problem. The first problem includes strategic innovation dilemmas, the second problem concerns how these innovations are operationalized, and consequently the third problem concerns how the organization will facilitate this operationalization. These problems are handled differently depending on the topology of an organization, with the typical topologies being defenders, prospectors, analysts, and reactors. The defenders are generally good at a specific niche and do not pursue new opportunities in a changing market. They tend to focus on the engineering/operational problem. The prospectors are continuously experimenting with new things and, thereby, focus on the entrepreneurial problem. The analyzers are in between defenders and prospectors, both safeguarding their current products and developing new ones. Finally, the reactors do not know what to do with innovations and wait until they can wait no longer. Overall, Miles et al. (1978) thus view strategies as hybrid. This is in line with the body of literature who emphasize that rushing to embrace a disruptive innovation can be detrimental for established companies when other responses, including ignoring the innovation, make more (economic) sense Charitou and Markides (2003); Christensen et al. (2006); Epicoco (2016); Hang et al. (2015); Si and Chen (2020).

Sustainable business model implementation strategies

Given their ESG scores, we classified the best 20% (i.e., top 4) banks as already having a sustainable business model (see Table 3.2). These banks were thus latent players in the simulation model. To conceptualize sustainable banking implementation strategies for the remaining banks, we designed a grid with two dimensions that influence a bank's strategic decision-making (see Figure 4.1). The first dimension concerned the trade-off between efficiency- and value-led (i.e., sustainable) operation, thereby representing the bank's strategic decision on costs or differentiation as suggested by Porter (1980). The second dimension represented the urgency that is given to implementing the sustainable business model. To validate and relate the grid to existing literature, we also plotted the topologies of Miles et al. (1978) on the grid.

The grid was consequently sampled to design six possible implementation strategies with their own logic behind reaching a decision on adopting a sustainable business model (see Table 4.2). Note that the grid was left empty in the lower-right, as it was not possible to be a leader while not implementing a sustainable business model. In addition, we positioned the Adapter strategy as equally slow as Threshold and Nothing. This is because the Adapter is slow in its implementation, while it still might choose to adopt a sustainable business model before the other two strategies. In theory, Threshold and Adapter could thus become sustainable at the same time step.

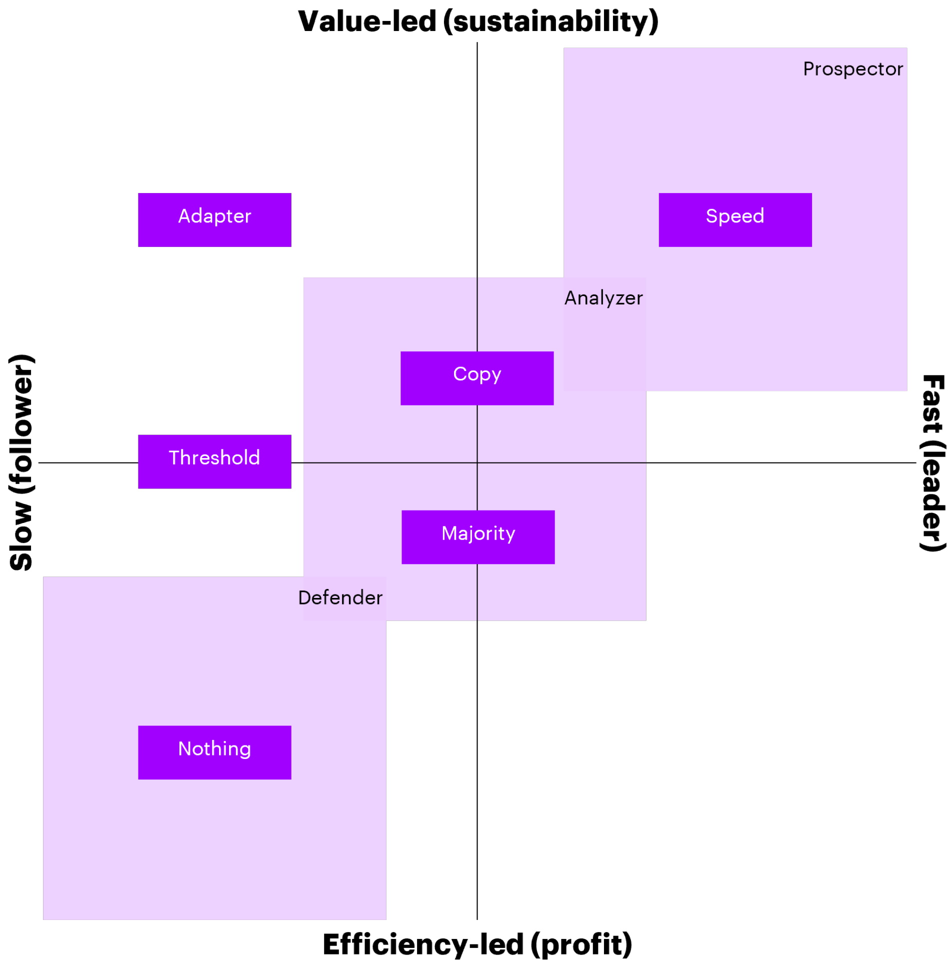

FIGURE 4.1: Grid with two dimensions that influence a bank's strategic decision-making. The first dimension was based on Porter (1980).

TABLE 4.2: Sustainable banking implementation strategies.

Implementation strategy	Description	Goal of strategy	Implication
Speed	Bank values sustainability and perceives a business opportunity. The bank therefore wants to become sustainable a.s.a.p	Profit from the disruptive innovation	Bank starts the implementation period within the first year of the simulation

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Implementation strategy	**Description**	**Goal of strategy**	**Implication**
Adapter	Bank values sustainability and perceived a business opportunity, but needs more time to implement the sustainable practices throughout its organization	Profit from the disruptive innovation	Bank starts the implementation period within the second year of the simulation and has an elongated implementation period
Copy	Bank is open to becoming sustainable if its direct competitor is doing so. They will thus try to erode the advantage of a competitor.	Prevent losing market share relative to competitor from the same banking category.	If a predefined bank from the same bank category becomes sustainable, the bank also becomes sustainable. The implementation period will be shorter as one can 'steal' the ideas.
Majority	Bank is open to becoming sustainable, but only if it is necessary to stay relevant.	Prevent degradation to a different bank category and stay relatively popular.	If the majority of the banks in a particular bank category are sustainable, then the bank also becomes sustainable.
Threshold	The bank values its market share and will only become sustainable if its market share is falling too much to stay competitive.	Maintain market share	Threshold has to be predefined.
Nothing	Bank does not perceive sustainability as a business opportunity	No costs for innovation	Bank will not become sustainable throughout the simulation.

Dynamics in the sustainability feature score

If a bank decided to become sustainable during the simulation, its sustainability feature score was linearly increased during a so-called implementation period (with a default length of one year) to a predefined value. This latter value was randomly generated from a custom beta distribution (see Figure 4.2).

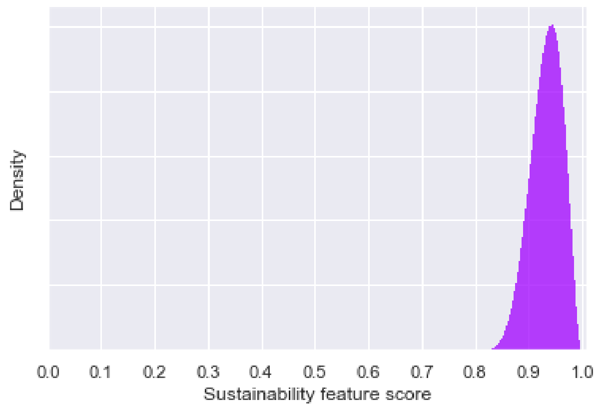

FIGURE 4.2: Beta distribution with parameters alpha=6 and beta=3.

4.2.2 Exogenously modeled bank dynamics

In accordance with trends in the retail banking industry, the digital and price feature values were made to be dynamic. The service feature value was not made dynamic, as we observed that they have been historically stable (Ipsos, 2022). We note that while in theory these dynamics could also be modeled endogenously via autonomous decisions of bank managers, but this was out of the scope of the simulation model.

Dynamics in the digital feature score

In the system inventory, we found that the differences between digital competences of banks are expected to become smaller over time as digital services are commoditized. We therefore increased the digital feature score for every bank at every time step. Specifically, for each bank, we generated 28 random numbers from a uniform distribution on the interval [digital feature score at t=0, 1 (the maximum feature score)]. Next, these numbers were sorted in ascending order. At every time step, the digital feature score was increased to the next number in the sequence. This approach advantageously allowed banks to potentially gain a digital feature score higher than their competitor if they did not have this at the start of the simulation.

Dynamics in the price feature score

In the system inventory, we furthermore found that monetary (switching) incentives change on a quarterly basis. As such, we modeled them using a small Markov chain model (see Figure 4.3). A Markov model is a stochastic model describing a sequence of possible events in which the probability of each event depends only on the previous event, i.e., whether there was a monetary incentive in the previous quarter (Berg, 2005). This dependence on a past event made a Markov chain a superior approach to using a simple random chance, which does not account for the past. The Markov chain model was designed to generate a 50% change that a bank offered a monetary incentive if it did not do so in the previous quarter (20% chance on £5 incentive, and a 10% chance for a £20, £125, or a £150 incentive). If there already was a monetary incentive, there was a 30% or 20% chance that it was extended into the next quarter for the smaller or bigger incentives, respectively.

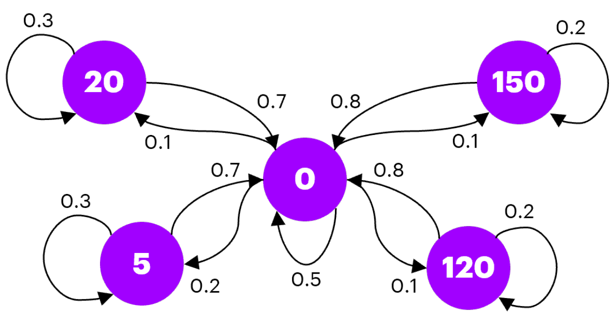

FIGURE 4.3: Markov chain model to determine monetary incentive per quarter. Probabilities to transition from one state (purple circle) to another are indicated on the arrows. Each state indicates the magnitude of the monetary incentive.

4.3 Modeling the consumer choice of bank behavior

The conceptualization to this point dictated that the consumer choice of bank behavior had to be conceptualized with regard to the bank features, i.e., with how the attractiveness of banks was modeled. Below, we elaborate on the specific steps that were taken to this end.

4.3.1 Bank feature weights

By taking the average importance of bank features to the consumer choice of bank based on the consumer surveys in section 3.3, we observed that not every bank feature is equally influential on the consumer choice of bank. In addition, the system inventory showed that there are discrepancies between reasons to leave or join a bank. To represent these observations, we obtained a $d = 4$-dimensional vector $\mathbf{w}$ describing a weight $\mathbf{w} = [w_1, \ldots, w_d]$ for each feature with $d \in ['sustainability', 'Digital', 'price', 'Service']$. For customer attrition and acquisition, the weight vectors were $\mathbf{w_{attrition}} = [0.1, 0.1, 0.1, 0.7]$ and $\mathbf{w_{acqusition}} = [0.2, 0.3, 0.3, 0.2]$, respectively.

4.3.2 Attrition and acquisition scores

Using the bank feature weights, we effectively summarized the consumer behavior towards a particular bank into one arbitrary number between 0-1. This summarizing step was performed separately towards customer attrition and acquisition, as both depended on separate bank feature weights. Specifically, for every player n in the game, we obtained at every time step t a $d = 4$-dimensional vector $\mathbf{v_n}(t)$ which contained the scaled bank features (i.e., with a value between 0-1) $\mathbf{v_n}(t) = [v_n^{'Sustainability'}, \ldots, v_n^{'Service'}]$. This bank feature vector was multiplied component-wise with the attrition weight vector $\mathbf{w_{attrition}}$ over the $d = 4$ feature dimensions and consequently summed using:

$$attrition\_score_n(t) = (\sum_{i=1}^{d} \mathbf{w^i_{attrition}} * (1 - \mathbf{v}^i_n(t))) \tag{4.1}$$

to obtain an "$attrition\_score_n(t)$" $in\, \mathbb{R}^1$ that represented some arbitrary number between 0-1 with a relative magnitude to the scores of the other n players in the game (see Figure 4.7). The higher the score, the more customer attrition a bank should suffer. Note that the values in the feature vector were inverted, as a better performance on the bank features represented more favorable consumer behavior, and thus less customer attrition.

In addition, at every time step t an "$acquisition\_score_n(t)$" $in\, \mathbb{R}^1$ was calculated similar as to how the "$attrition\_score_n(t)$" was calculated, with the difference being the use of $\mathbf{w_{acquisition}}$ instead of $\mathbf{w_{attrition}}$ and not inverting the feature vector $\mathbf{v_n}(t)$:

$$acquisition\_score_n(t) = \sum_{i=1}^{d} \mathbf{w^i_{acquisition}} * \mathbf{v}^i_n(t) \tag{4.2}$$

4.3.3 Control variables to scale the attrition and acquisition score

Both the attrition and acquisition score resulted in an arbitrary number between 0-1 for every bank. This implied that a mid-tier bank with a similar attrition score as a big 4 bank has similar customer attrition, which was not valid. As such, we set out to find control variables that could be used to scale the attrition/acquisition score to make it a more realistic indicator of consumer attrition/acquisition per bank. Selecting these control variables was subject to two criteria: (i) they should be adaptive to the current state of the system (i.e., depend on time t), and (ii) they should represent a concept that is relevant during the entire simulation time. So, for instance, assigning the digital challengers with some sort of "innovative" score was neither time dependent (because it is unknown what the dynamics are in the score over time), nor sufficiently relevant (as the digital challengers are already losing their uniqueness).

Towards customer attrition, we identified the number of customers per bank to be a suitable control variable as we found during the system inventory that the historical market share relatively linearly correlated with customer attrition (see Figure B.6, Spearman Coefficient: 0.74, p-value: 4.3e-4, and Figure 4.7). Towards customer acquisition, however, the number of customers could not be used as a control variable as the market share insufficiently linearly correlated with customer attrition (see Figure B.6, Spearman Coefficient: 0.68, p-value: 1.9e-3). Instead, based on expert advice (Expert 2), we determined a promotional score that represented the fact that banks with more marketing attract more customers (Alnsour, 2013). To this end, we used Google Trends statistics that indicated how often "[bank name] + current account" was searched for within the UK in the past 12 months. By plotting this statistic against the number of customers (which was advantageously time dependent in the model), we fitted a second-order polynomial (see Eq. 4.3, a=-0.19, b=5.35, and c=0.35) that could be used as a control variable. That is, depending on the number of customers, a promotion score was generated that was used to scale the acquisition score.

4.4 Modeling customer attrition and acquisition per bank

The consumer choice of bank behavior gives rise to PCA market growth and switching volumes. However, due to lacking insights into consumer behavior, we could not directly leverage the attrition/acquisition score per bank into endogenously modeling PCA market growth and switching volumes. Instead, we modeled PCA market growth and switching volumes in an exogenous manner and consequently determined the origin of these customers by distributing them among the banks. This latter distribution was, in turn, modeled endogenously based on the integration of methods from the previous section.

4.4.1 Quantifying PCA market growth

In the system inventory, we predicted that the PCA market would grow to 2.0 PCA per Capita (uncertainty interval [1.9; 2.1]) by the end of the simulation time. As there will be c.56 million UK adults at the end of the simulation time, the expected number of PCAs in the market at the end of the simulation was 56 million * 2.0 = 112m PCAs (Office of National Statistics, 2021). To project the number of PCAs in the market throughout the simulation, we fitted a second order polynomial on three historical data points from FCA (2022a) and on our predicted data point:

$$n_{PCA}(t) = at^2 + bt + c \tag{4.3}$$

in which 'a' represents the width of the parabola, 'b' the horizontal offset, and 'c' the vertical offset (see Figure 4.4, Table B.2). The curve was fitted using the Numpy Libary in Python which functions by minimizing the sum of the squared errors (Oliphant, 2006; Portnoy and Koenker, 1997). Including the historical datapoints served the purpose of guiding the fit into a logarithmic-shape curve that represented the expected stall in market growth with sufficient accuracy. The number of PCAs in the market was thus dictated by a fitted second-order polynomial curve that changed for every run depending on the expected numbers of PCA per capita. Consequently, the number of additional PCAs available to consumer acquisition at time step 't' was given by the difference in PCA market size relative to the previous time step:

$$\Delta n_{PCA}(t) = n_{PCA}(t) - n_{PCA}(t-1) \tag{4.4}$$

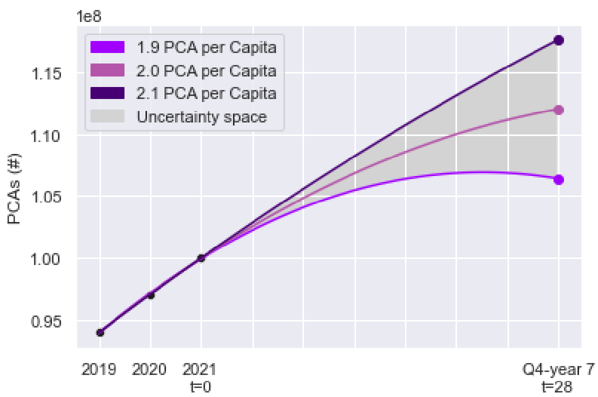

FIGURE 4.4: Predicted PCA market growth. Points with the timestamps '2019', '2020', and '2021' are taken from FCA (2022a) (black). Point '2021' also represented the initial condition of the model (t=0). Timestamp 'Q4-year 7' represents the end of the simulation time (t=28). The values at the latter timestamp represent different possible future values (different shades of purple). Datapoints were fit using a second-order polynomial. The uncertainty space represents all possible manifestations of where the growth projection may be (grey area).

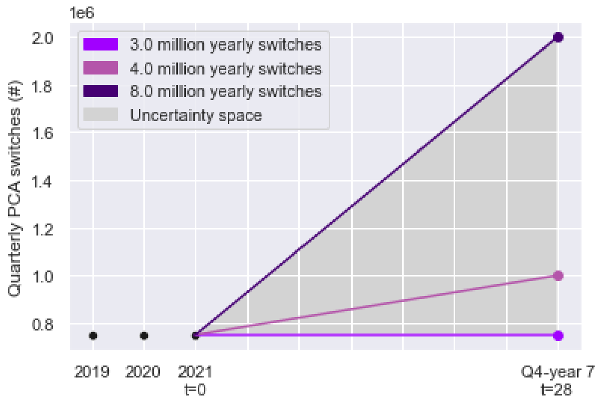

FIGURE 4.5: Predicted future switching volume. Points with the timestamps '2019', '2020', and '2021' are guestimated historical switching volumes (black). Point '2021' also represented the initial condition of the model (t=0). Timestamp 'Q4-year 7' represents the end of the simulation time (t=28). The values at the latter timestamp represent different possible future values (different shades of purple). Datapoints were fit using a first-order polynomial. The uncertainty space represents all possible manifestations of where the growth projection may be (grey area).

4.4.2 Quantifying future switching volumes

We predicted that the future switching volume would grow linearly with an uncertainty interval of [3M; 8M] by the end of the simulation time. This translated to quarterly switching volumes of [0.75m; 2m]. To project the switching volume throughout the simulation, we fitted a first order polynomial on the guesstimated historical switching volume and on our predicted data point:

$$n_{switches}(t) = at + b \tag{4.5}$$

in which 'a' represents the slope of the curve and 'b' the vertical offset (see Figure 4.4, Table B.2). The curve was fitted in the same manner as the PCA market growth projection, i.e., by minimizing the sum of the squared errors. The total customer attrition volume at time step t was thus given by the fitted curve Eq. 4.5.

4.4.3 Payoff function customer attrition and acquisition

To determine the customer attrition and acquisition per bank during the simulation, we multiplied the attrition/acquisition score with its control variable and determined the relative size of this quantity to the quantities that describe all the banks. Specifically, for every bank n at every time step t, the customer attrition was calculated by multiplying the ratio of the $attrition\_score_n(t)$ relative to the total $attrition\_score(t)$ among all the banks with the switching volume $n_{switches}$ using:

$$n\_attrition_n(t) = n_{switches}(t) * \frac{attrition\_score_n(t) * n^n_{customers}(t)}{\sum_{j=1}^{n} attrition\_score_j(t) * n^j_{customers}(t)} \tag{4.6}$$

in which the $n^n_{customers}(t)$ was used as a control variable (see Figure 4.7). Similarly, the customer acquisition was calculated using:

$$\begin{aligned} n\_acquisition_n(t) = (n_{switches}(t) + \Delta n_{PCA}(t)) * \\ \frac{acquisition\_score_n(t) * PROMO(n^n_{customers}(t))}{\sum_{j=1}^{n} acquisition\_score_j(t) * PROMO(n^j_{customers}(t))} \end{aligned} \tag{4.7}$$

in which the PCA market growth Δn_{PCA} presented additional customers available for acquisition besides the ones that were switching their bank, and $PROMO(n^n_{customers}(t))$ was used as a control variable.

4.5 Overview of conceptualization

All in all, the conceptual model has been transformed into the following blueprint for a situation model: (1) the modeler should define relevant bank features that represent the attractiveness of a bank, and next quantify these features using proxies; (2) the autonomous and endogenous behavior of banks has to be defined by multiple implementation strategies; (3) For every time step t in the simulation, an attrition- and acquisition score is determined per bank that represents the consumer choice of bank behavior; (4) Based on the exogenous PCA market growth and switching volume, the bank customer attrition and acquisition (i.e., their payoff) is determined; (5) Based on the state of the system (e.g., how many banks have adopted a sustainable business model) and/or the self (e.g., lower threshold on market share), the banks make a strategic decision on whether to become sustainable; and (6) The competitive position of banks is updated based on their previous strategic decision and exogenous modeled retail banking industry trends. As such, this blueprint answers SQ4, which concerned the question of how the effect of consumer and bank behavior on the number of customers per bank can be modeled.

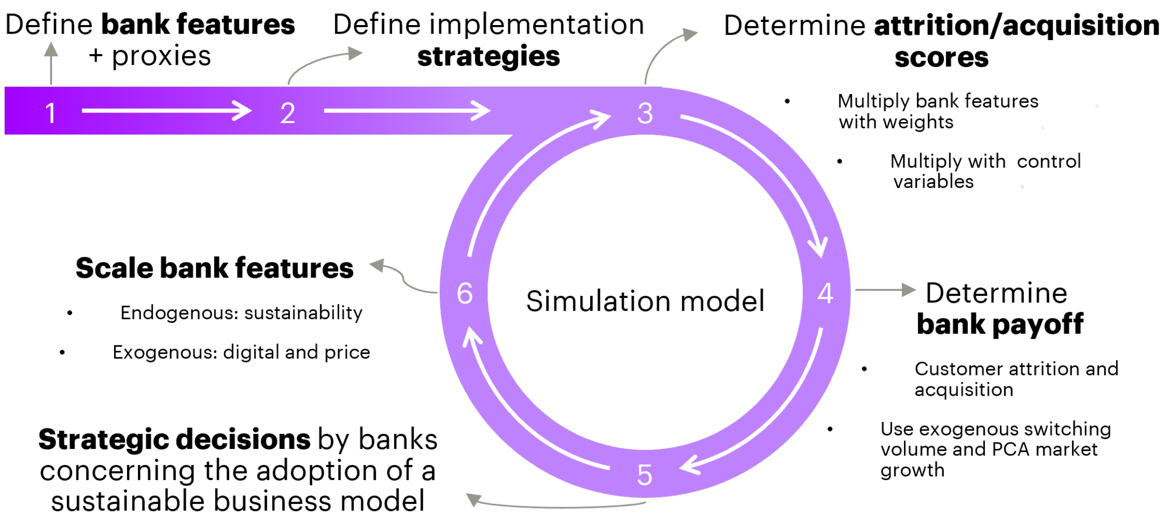

Figure 4.6: Blueprint for the simulation model in which it is defined which input is needed for the model (step 1 and 2) and which processes take place during the simulation (step 3 to 6).

1. Select proxies for bank features

	Sustainable1	Sustainable2	Digital1	Digital2	Price1	Price2	Service1	Service2
Bank A	65	12	4.3	89	0	55	70	67
Bank B	45	38	3.2	67	150	65	N.A.	82
Bank C	42	17	N.A.	77	20	78	68	76
Bank D	56	14	4.6	78	0	81	77	78

2. Make proxies compatible by scaling them between 0-1

	Sustainable1	Sustainable2	Digital1	Digital2	Price1	Price2	Service1	Service2
Bank A	1	1	0.79	1	0	0	0.22	0
Bank B	0.13	0	0	0	1	0.38	-	1
Bank C	0	0.81	-	0.45	0.13	0.88	0	0.60
Bank D	0.61	0.93	1	0.50	0	1	1	0.73

Note that sustainable2 was inverted as a low score represented better performance, which contracted with sustainability1

3. Take average of proxies to get bank feature scores

	Sustainable	Digital	Price	Service
A	1	0.90	0	0.11
B	0.07	0	0.69	1
C	0.41	0.45	0.50	0.30
D	0.77	0.75	0.50	0.87

	Sustainable	Digital	Price	Service
A	0	0.10	1	0.89
B	0.93	1	0.31	0
C	0.59	0.55	0.50	0.70
D	0.23	0.25	0.50	0.13

Invert the bank feature scores when calculating the attrition score as a better performance on the bank features represent more favorable consumer behavior, and thus less attrition

4. Multiply bank feature scores with feature weights to get an acquisition / attrition score

	Acquisition score
A	0.49
B	0.42
C	0.43
D	0.70

W$_{acquisition}$ = [0.2 0.3 0.3 0.2]

Ex. Bank A: 0.2*1 + 0.3*0.9 + 0.3*0 + 0.2*0.11 = 0.49

	Attrition score
A	0.73
B	0.22
C	0.65
D	0.19

W$_{attrition}$ = [0.1 0.1 0.1 0.7]

Ex. Bank A: 0.1*0 + 0.1*0.1 + 0.1*1 + 0.7*0.89 = 0.73

5. Use control variables to determine banks' contribution to acquisition / attrition

$$\text{Share acquisition}_{\text{Bank A}} = \frac{\text{Attrition score}_{\text{Bank A}} * \text{PROMO}(\text{n\_customers}_{\text{Bank A}})}{\sum_{i=\text{Bank A}}^{\text{Bank D}} \text{Attrition score}_i * \text{PROMO}(\text{n\_customers}_i)}$$

$$\frac{0.49 * 20}{0.49 * 20 + 0.42 * 10 + 0.43 * 35 + 0.70 * 15} = 25\%$$

$$\text{Share attrition}_{\text{Bank A}} = \frac{\text{Attrition score}_{\text{Bank A}} * \text{n\_customers}_{\text{Bank A}}}{\sum_{i=\text{Bank A}}^{\text{Bank D}} \text{Attrition score}_i * \text{n\_customers}_i}$$

$$\frac{0.73 * 4M}{0.73 * 4M + 0.22 * 2M + 0.65 * 10M + 0.19 * 3M} = 28\%$$

6. Calculate customer attrition and acquisition per bank

n acquisition $_{\text{Bank A}}$ = Share acquisition $_{\text{Bank A}}$ * (n_switches + market growth)

n attrition $_{\text{Bank A}}$ = Share attrition $_{\text{Bank A}}$ * n_switches

FIGURE 4.7: Serial steps taken to calculate customer attrition and acquisition per bank.

Chapter 5

Model formalization

In this chapter, we describe how we formalized the model into a set of exact rules based on the conceptualized model concepts (Van Dam et al., 2012). To this end, we implemented the simulation model in Python 3.9 using the MESA library (Masad and Kazil, 2015). The structure in this chapter is according to the Overview, Design concepts, and Details (OOD) protocol that is typically used to communicate ABM models Grimm et al. (2006). First, in section 5.1, we describe the purpose and the agents in the model. In section 5.2, we elaborate on the model narrative, which explains which bank does what with whom and when. In section 5.3, we address the used design concepts. Finally, section 5.4 addresses the model details. This chapter thereby does not answer any specific SQ, but rather reports on the execution of SQ4 (i.e., how to model relevant consumer and bank behaviors in the system).

5.1 Simulation model overview

5.1.1 Purpose of the model

We constructed this simulation model to explore the strategical decision-making of UK bank managers in a competitive environment by the effect that these decisions have on the PCA market share dynamics. For this purpose, we used the model as a laboratory for testing the relative effect of different sustainable banking implementation strategies, and for the exploration of alternative future scenarios depending on the uncertainties in variables that characterize the UK retail banking industry.

5.1.2 Model entities, state variables, and scales

We represented each bank by an 'agent' in the model, and characterized this agent by its own state variables that tracked the number of customers as well as the transition to becoming sustainable throughout the simulation (see Figure 5.1). The model comprised a total of seven agent types, with each type of agent representing a different sustainable banking implementation strategy. To put it in game theory terms, each of the players (i.e., banks) thus had seven strategies at its disposal. The strategy that each player adopted was determined randomly at the initialization of the model, although we also told the model upfront how often each strategy could be assigned.

Each agent had a staging step() method in which decisions ('when') were made based on available information from self and the system, and an advance() method which executed these decisions. As every sustainable banking implementation strategy had its own logic behind making decisions (see Table 4.2), we modeled every strategy (i.e., agent type) as a child class with a unique 'step()' method.

We furthermore implemented some additional attributes specific per agent type to ensure its proper functioning. Specifically, we assigned agents of the type 'Speed' and 'Adapter' a random time step within the first or the second year of the simulation, respectively, using a uniform interval. This time step indicated when they decided to adopt a sustainable business model. A 'Majority' agent based its decision to adopt a sustainable business model on the decisions of the other banks within the same bank category (e.g., the scale challengers). That is, it became sustainable if half of its competitors decided to do so. Similarly, an agent of type 'Copy' monitored one specific competitor from the same bank category and adopted a sustainable business model if this specific competitor did so. An agent of the type 'Threshold' adopted a sustainable business model if its market share was 90% of the size at the model initialization. Finally, an agent of type 'Nothing' did not adopt a sustainable business model and thus required no decision to be made, which is modeled by an empty step() and advance() method. Similarly, if an agent had become sustainable, it was modeled as a 'Latent' agent, which would also no longer make any decisions.

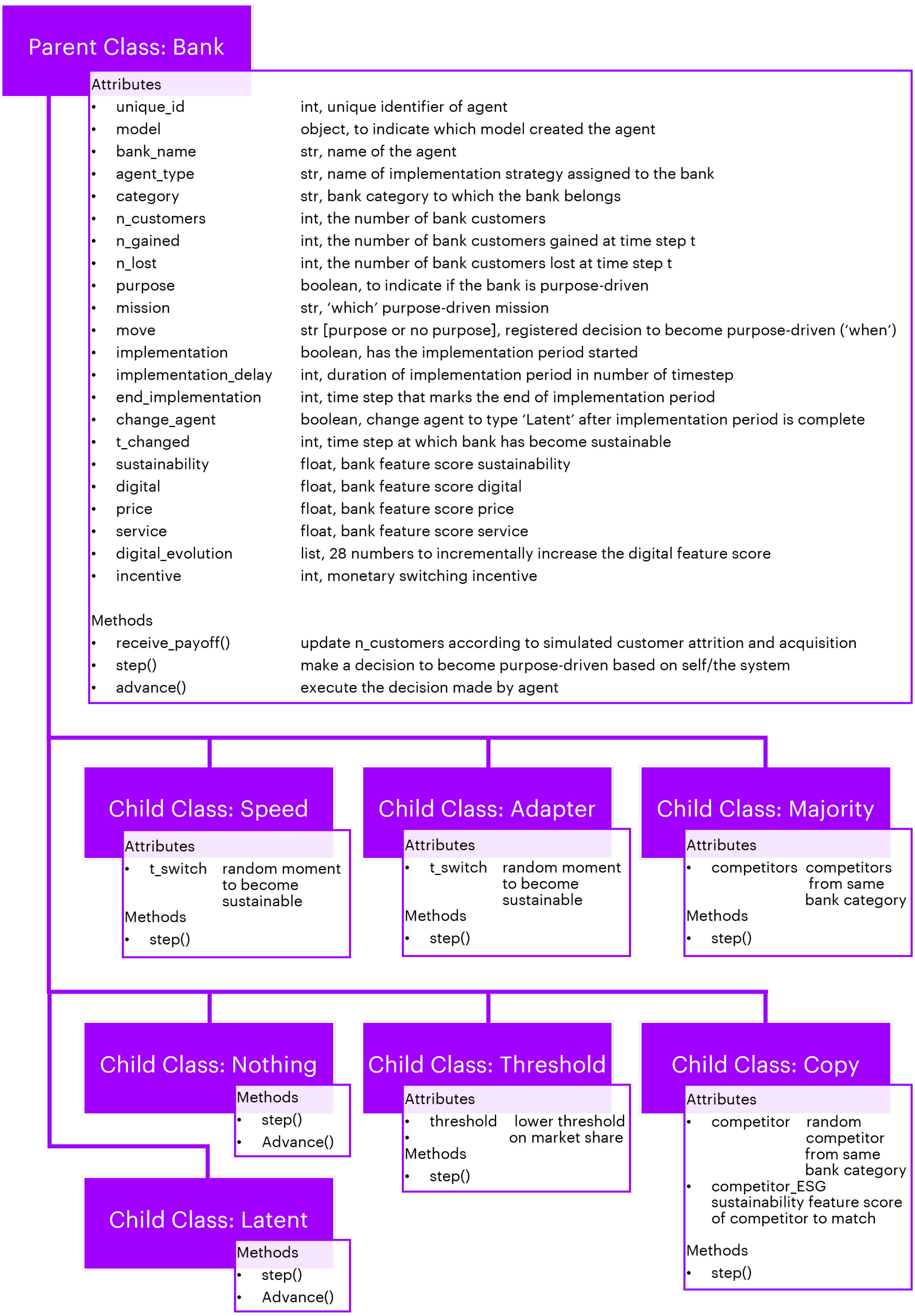

FIGURE 5.1: Attributes and methods of each agent type. Child classes inherit all attributes and methods of the parent class, although every child class overwrites the step method of the parent class. In addition, some child classes have additional attributes (e.g., 'Speed').

5.1.3 Simulation time

The simulation timeframe was seven years with quarterly time steps, as this is consistent with data reporting from the UK retail banking industry. There were thus 28 time steps in the model, with t=0 indicating the initial state of the system and t=28 indicating the end of Q4, year 7. The base year was consistent with 2021, meaning that the simulation corresponded to a period of 2021-2028.

5.2 Process overview and scheduling

At every time step, a number of processes took place for every agent. In general, an agent was in one of three states: active, implementation, or latent (see Figure 5.2). The states referred to how far along the banks were in becoming sustainable. In every state, the agents first received their payoff (i.e., customer attrition and acquisition) and consequently had their digital and price features scaled (exogenously). The processes that followed were state dependent.

In the active state, agents could make the decision to become sustainable or not. If the agent decided not to, they remained in the active state, and otherwise they initiated their sustainable banking implementation period. During this period (lasting 4 time steps by default), agents were in the implementation state in which their sustainability feature score increased. If the agent had completed its sustainable banking implementation period, it entered the latent state, which entails that the bank had become sustainable. As such, agents made a decision not in favor of a sustainable business model at every time step until they decided to adopt the sustainable business model (if they even did at all). After this one "positive" decision towards adopting a sustainable business model which is made in the active state, the agents thus no longer made decisions.

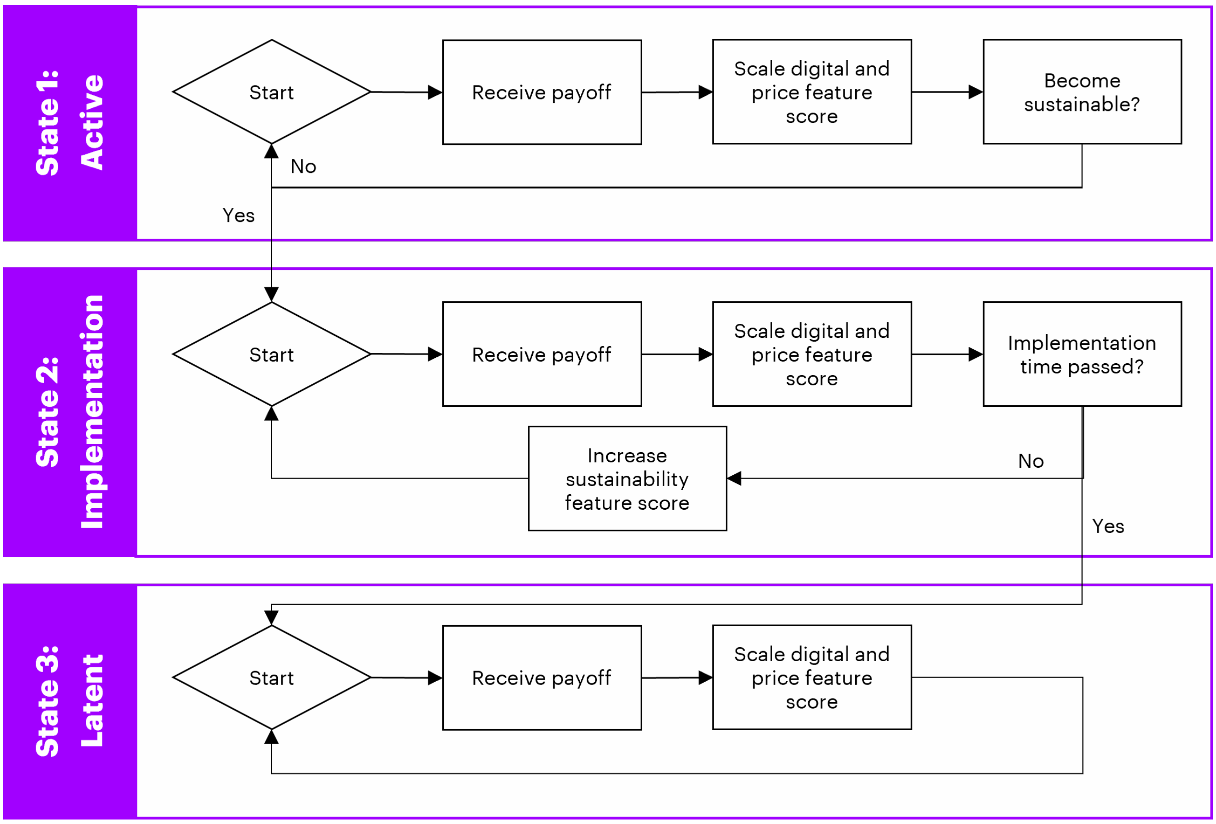

FIGURE 5.2: Different states an agent can be in and the actions happening to them at every time step. 'Start' indicates the start of every time step.

To mimic all agents making decisions simultaneously at every time step, we used the MESA scheduler "Simultaneous Activation" (Masad and Kazil, 2015). This scheduler lets all agents make a decision according to their step() method, after which these decisions are executed using the advance() method. This effectively prevented path dependency in the agent decision-making processes, i.e., certain agents making decisions with more information as other agents have already made decisions.

5.2.1 Model components

The model had various state attributes that dictated the processes in the simulation, such as the number of iterations, the duration of the implementation period, PCA market growth, and switching volumes (see Figure 5.3). In addition, the model had methods to guide the calculations and processes that are executed at every time step.

Class: Game_Retail_Banks

Attributes	
• seed	int, random seed
• num_iterations	int, simulation time
• implementation_delay	int, duration of implementation period in number of time steps
• agents	list, inventory of active agents in the model
• attrition_feature_weights	list, vector $w_{attrition}$ with weights
• acqusition_feature_weights	list, vector $w_{acqusition}$ with weights
• list_missions	list, inventory of possible purpose-driven banking missions
• pca_growth_pred	fitted curve, pca market growth prediction, curve gives #pca at time t
• switching_volume	fitted curve, switching volume prediction, curve gives #switches at time t
• schedule	MESA scheduler, for the activation of agents during the simulation
• datacollector	MESA datacollector, for collecting model and agent statistics during the simulation
• banks_per_category	dict, list of banks assigned to each bank category
• feature_matrix	matrix, contains the scaled bank features
• market_shares	dict, market share per bank category
• t	int, time step

Methods	
• payoff_func_attrition()	determine customer attrition per bank
• payoff_func_aqcuisition()	determine customer acquisition per bank
• step()	advance the model by one step, i.e. determine payoffs, scale features, and execute agent decisions
• scale_digital()	scale the digital feature score for every bank
• scale_price()	scale the price feature score for every bank

FIGURE 5.3: Attributes and methods of the simulation model.

5.3 Design concepts

We used several relevant typical ABM design concepts in the model (Grimm et al., 2006):

- Emergence: market share dynamics changed based on the lower-level decisions of banks. That is, banks could actively decide to influence their sustainability feature score as a means to potentially improve their attrition and acquisition scores relative to their competitors. These interactions resulted in higher-level dynamics in the customer market shares.

- Adaptation: part of the agents had an implementation strategy in which the decision depended on market developments (i.e., agents of type 'Majority', 'Threshold', and 'Copy'). Their response is thus adaptive to the system.

- Objectives: agents objectives depended on their implementation strategy, see Table 4.2.

- Sensing: all banks were assumed to know their own characteristics. This information informed banks' decisions. In addition, banks could observe which other banks were sustainable, but no other industry characteristics (such as market shares of competitors) could be observed.

- Stochasticity: multiple processes and decisions have been modeled via a stochastic component, such as the scaling of the digital and price feature score, the increase in the sustainability feature score once a bank decided to become sustainable, temporal moments when banks decided to become sustainable, the choice of a competitor to copy, and assigning banks with a particular implementation strategy at the model initialization.

- Collectives: every bank was assigned to a banking category; either the big 4, scale challengers, mid-tier, or digital challengers.

5.4 Model Details

5.4.1 Model initialization

During the initialization of the model, we fitted the curve for PCA market growth, switching volumes, and for the acquisition score control variable. Next, we created agents based on an input dataset containing bank statistics (such as their bank features) (see Table B.4). A total of 20 banks were included, of which 4 were classified as Latent at the initialization.

5.4.2 KPIs

We used a MESA data collector to tracks multiple model- and agent KPIs throughout the simulation. Specifically, the number of customers per bank and when they decided to become sustainable was monitored.

5.4.3 Assumptions

The simulation model is dependent on numerous assumptions, which we have listed and discuss in Appendix C. In short, there were various assumptions that underlay the quantities that we used for model variables, including for the current PCA market share per bank, the proxies used for the bank features, and the exogenously modeled market growth and switching volumes. Most of these variables have been estimated based on expert advice, rendering their accuracy likely to be decent. In addition, the uncertainties in PCA market growth and switching volumes are addressed by sampling them using EMA, which effectively mitigates the implications of inaccurate predictions. The model design further assumed that there are no delays in processes. So, for instance, that all consumers that switch their bank account, open a bank account at another retail bank in the same time step.

5.4.4 Submodels

This model did not include any submodels.

Chapter 6

Results

In this chapter, we report on the dynamics in PCA market shares that emerge from different possible manifestations of variables in the UK retail banking industry. To this end, we first discuss the experimental setup that we employed during the simulations in section 6.1. In section 6.2, we present the model outcomes that resulted from the open exploration of the uncertainty space. Next, in section 6.3, we employed a directed search to identify variables that significantly contributed to model outcomes of interest. Finally, in section 6.4, we present the model outcomes that resulted from special scenarios with shock events. The results presented in this chapter thereby answer SQ5.

6.1 Experimental setup

To model all possible developments within the system (i.e., all future states), we experimented with the scenario space. Specifically, each variable that could vary (e.g., PCA market growth) represented a dimension, and each point in that multidimensional space presented a possible condition that the system may experience (see Table 6.1). Note that the bank feature weights were always normalized to sum to 1 and, as we included 20 banks in the simulation including four Latent players, the number of banks with a certain implementation strategy was always normalized to 16. We created a total of 400 scenarios using Latin Hypercube Sampling (LHS) of the uncertainty space, and we repeated each of these scenarios 30 times to account for the stochasticity in the model. We thus ran the model 12,000 times.

Furthermore, we visualized the model outcomes only from the perspective of traditional banks (i.e., big 4 banks). These type of banks are at the forefront of the sustainable banking transition together with scale challengers and mid-tier banks, but have the additional property of scale. That is to say, aiding traditional banks in becoming sustainable via corporate policy advice has the biggest impact on the planet, as the influence of their externalities is the most extensive. In line with this research's objective to advise both bank managers and regulators, we therefore focused on investigating these banks.

TABLE 6.1: Parameter ranges of system uncertainties.

Variable name	**Lower limit**	**Normal value**	**Upper limit**
PCA per capita	1.9	2.0	2.1
Quarterly switching volume	0.75	1	2
$\text{Weight}_{\text{acquisition}}$ sustainable feature	0	0.2	0.8
$\text{Weight}_{\text{acquisition}}$ digital feature	0	0.3	0.8
$\text{Weight}_{\text{acquisition}}$ price feature	0	0.3	0.8
$\text{Weight}_{\text{acquisition}}$ service feature	0	0.2	0.8
Implementation duration	2	4	8
Speed	0	N.A.	16
Adapter	0	N.A.	16
Copy	0	N.A.	16
Nothing	0	N.A.	16
Majority	0	N.A.	16
Threshold	0	N.A.	16

6.2 Open exploration of the uncertainty space

We first set out to investigate the effect of the system uncertainties on the dynamics in the customer market shares. To this end, we used open exploration of the entire scenario space. Impressively, these 12,000 model runs finished in approx. 3 minutes using multicore processing on a DELL laptop with an 11th Gen Intel(R) Core(TM) (i5-1145G7 @ 2.60GHz 1.50 GHz) with eight logistical processors.

The market share of the big 4 banks decreases during the simulation time with a scenario dependent curve

We observed that the PCA market share of the big 4 banks is both behaviorally and numerically sensitive to the system uncertainties (see Figure 6.1). Specifically, the curve in the decrease in market share differed per scenario. All scenarios resulted in a relatively linear decrease in the market share in the first simulation years (year 1-2), but, depending on the scenario, this decrease in market share either stabilized or continued (with a less steep slope) towards the end of the simulation. As a result, we observed increased variance among the model outcomes towards the end of the simulation. Specifically, we observed a four-fold numerical difference between the worst case scenario (market share decrease from 0.610 to 0.590) and the best case scenario (market share decrease from 0.610 to 0.604), although the absolute magnitude of this difference is quite small.

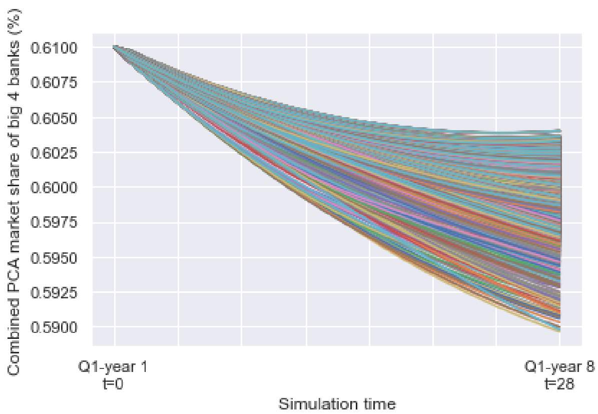

FIGURE 6.1: PCA market share dynamics of the big 4 banks as generated by the open explorations of 400 scenarios with 30 repetitions each.

Big 4 banks and scale challengers lose market share to mid-tier banks

We made similar observations for the market share dynamics of the other bank categories (see Figure B.8). Specifically, the market share of the scale challengers also slightly decreased, with smaller variance in the model outcomes as for the big 4 banks (decrease from 0.270 to value in range 0.262-0.266). On the other hand, the market share of the digital challengers slightly increased with little variance in the model outcomes (increase from 0.070 to value in range 0.073-0.077), and the market share of the mid-tiers increased with the largest variance among the model outcomes (increase from 0.050 to value in range 0.057-0.066). These observations indicated that the mid-tier banks largely absorbed the loss in market share by the big 4 banks and scale challengers.

Small subsidiaries within the big 4 category gain customers whereas large subsidiaries are losing them

Underlying the market share dynamics of the big 4 banks, were the market share dynamics of all the subsidiaries that grouped into this bank category. That is, the big 4 category comprised four big banking groups that contained multiple subsidiaries, resulting in a total of 9 banks within in the big 4 category (see Table 3.1). We observed that the market share of the smallest subsidiaries (1% market share at t=0) increased (c.0.5%), remained constant for the middle-sized subsidiaries (3-4% market share at t=0), and decreased (c.0.7%) for the larger subsidiaries (7, 8, 10, 13, or 14% market share at t=0) (see Figure 6.2). As the big 4 market share is the sum of these individual market shares, these observations provided a partial explanation as to why the net decrease in the total market share of all banks within the big 4 category was small.

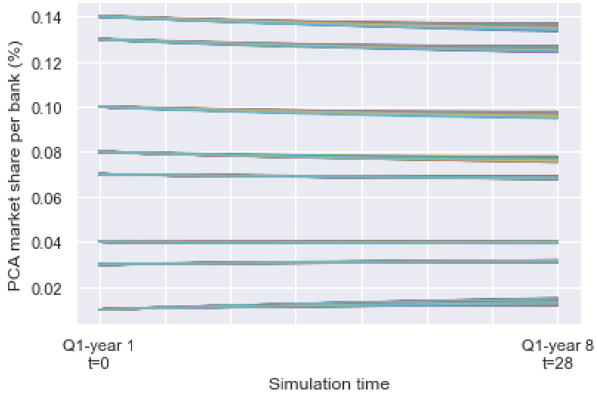

FIGURE 6.2: PCA market share dynamics per bank within the big 4 category as generated by the open explorations of 400 scenarios with 30 repetitions each. Note that there are two subsidiaries with a 1% market share at t=0, and as such their results cannot be distinguished from each other in this figure.

Not all banks became sustainable during the simulation

In the simulation model, the banks could actively decide to increase their sustainability feature score as a means to potentially improve their attractiveness to consumers, and, thereby, to decrease their attrition score and to increase their acquisition score. Given the loss in market share by the big 4 banks, we wondered if their response to the decrease in market share indeed was to adopt a sustainable business model. As such, we compared if and when (specific time step 't') big 4 banks became sustainable between the desirable outcomes (i.e., stabilization of the market share decrease and final market share > 0.602) and undesirable outcomes (i.e., final market share < 0.602). The analysis included a total of 9 banks * 12,000 model runs = 108,000 decisions.

We observed similar distributions for the desired and undesired outcomes, indicating that there were no temporal differences in the decisions to become sustainable (see Figure 6.3). Indeed, when testing for the distributional form of the variables we found no statistical significant finding (Mann–Whitney U test[1]: U1: 869569059, p-value: 0.10). Interestingly, we also observed that a significant amount of the big 4 banks did not become sustainable. In addition, the ones that did become sustainable usually made this decisions early on in the simulations, potentially underlying the previous observation that the system behavior started to change after year 2.

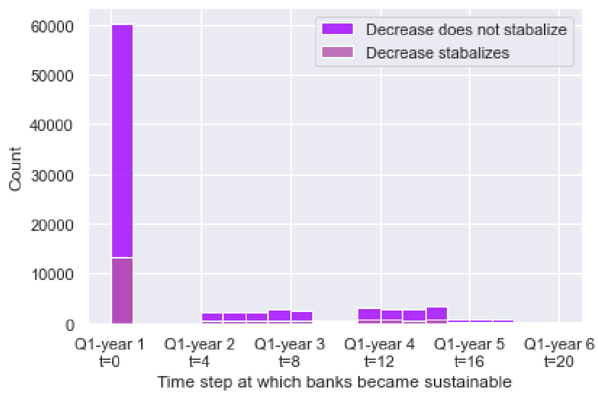

FIGURE 6.3: Temporal comparison of the big 4 banks' decisions to become sustainable between desired outcomes (i.e., final market share > 0.602, sample size = 19,539 decisions) (magenta) and undesirable outcomes (i.e., final market share < 0.602, sample size = 88,461 decisions) (purple). Banks that did not adopt a sustainable business model are indicated by 't=0'.

The observation that not all banks became sustainable during the simulation also applied to the other bank categories. Specifically, we calculated the total number of banks that considered becoming sustainable (i.e., all banks with one of the following implementation strategies: Speed, Adapter, Copy, Majority, or Threshold) and compared this statistic to the amount of banks that actually decided to become sustainable. We observed that none of the 12,000 scenarios led to all banks that considered becoming sustainable actually making the decision to do so (see Figure B.9). In addition, we observed that there were differences in the number of decisions in favor of a sustainable business model even if there was the same amount of "considerers". This latter observation hinted that there may be some other system characteristics that significantly influence the banks' decision-making process.

6.3 Scenario discovery for desired outcomes

In line with the previous observations, we set out to identify the scenarios (i.e., system uncertainties) that resulted in the desirable outcomes (i.e., market share > 0.602). To this end, we conducted scenario discovery using the Patient Rule Induction Method (PRIM) algorithm as incorporated in the EMA workbench. PRIM is a technique developed by Friedman and Fisher (1999) that iteratively narrows down the uncertainty space until "boxes" are found, each of which represents uncertainty intervals that can be statistically correlated to result in desirable outcomes. A PRIM box encompasses a good trade-off between coverage (what fraction of the total outcomes of interest are in the box) and density (what fraction of all cases in the box are actually of interest). In PRIM's attempt to increase the density-coverage measure by restricting uncertainty ranges, however, it could wrongly identify uncertainties that do not actually play a role in defining the outcomes of interest. Even so, PRIM is more easily interpretable than its alternative Classification and Regression Tree (CART) (Lempert et al., 2008).

Low PCA market growth and moderate to high consumer preference towards the banks' service quality significantly contribute to desirable outcomes

From the 12,000 model runs, we identified 2,310 outcomes of interest. To find the scenarios under which the model produced these desirable outcomes, PRIM identified two significant variables with an 71% coverage and 100% density (see Table 6.2A). That is, 71% of the outcomes of interests could be described with 100% accuracy by imposing restrictions on two dimensions: low PCA market growth and moderate to high consumer preference towards banks' service quality.

TABLE 6.2: PRIM scenario discovery results. The range indicates the values of uncertain variables that significantly contribute to desirable outcomes. This range is a subset of the total uncertainty interval of the variable as used as model input.

Uncertain variable	**Description**	**p-value**	**Significant range**	**Total uncertainty interval**
(A) PRIM results based on desired outcomes (market share > 0.602)				
PCA per capita	PCA market growth	1.68e-48	[1.90, 1.94]	[1.9, 2.1]
$\text{Weight}_{\text{acquisition}}$ service feature	Service feature weight	7.90e-45	[0.18, 0.65]	[0, 0.8]
(B) PRIM results based on top 5% best outcomes (market share > 0.603)				
PCA per capita	PCA market growth	3.75e-52	[1.90, 1.92]	[1.9, 2.1]
$\text{Weight}_{\text{acquisition}}$ sustainability feature	Sustainability feature weight	3.17e-13	[0.00, 0.27]	[0, 0.8]

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[1]The Mann–Whitney U test is a nonparametric test of the null hypothesis that, for randomly selected values X and Y from two populations, the probability of X being greater than Y is equal to the probability of Y being greater than X. The test does not rely on a normal distribution or equal sample sizes and is thus suitable for our data (McKnight and Najab, 2010).

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Uncertain variable	Description	p-value	Significant range	Total uncertainty interval
$\text{Weight}_{\text{acquisition}}$ service feature	Service feature weight	3.73e-32	[0.12, 0.65]	[0, 0.8]
$\text{Weight}_{\text{acquisition}}$ digital feature	Digital feature weight	1.99e-12	[0.15, 0.80]	[0, 0.8]
(C) PRIM results based on the desirable outcomes after a shock event (market share > 0.624)				
PCA per capita	PCA market growth	1.38e-49	[1.90, 1.93]	[1.9, 2.1]
$\text{Weight}_{\text{acquisition}}$ sustainability feature	Sustainability feature weight	8.01e-7	[0.00, 0.40]	[0, 0.8]
$\text{Weight}_{\text{acquisition}}$ service feature	Service feature weight	5.21e-21	[0.08, 0.76]	[0, 0.8]
$\text{Weight}_{\text{acquisition}}$ digital feature	Digital feature weight	4.49e-5	[0.03, 0.80]	[0, 0.8]
t_shock	The time step at which the shock event occurs	3.60e-28	[1, 26]	[1, 28]

Low PCA market growth, low consumer preference towards banks' sustainable operations, and moderate to high consumer preference towards banks' service quality and digital services significantly contribute to highly desirable outcomes

As the amount of desired outcomes was relatively high (2,310 outcomes of interest / 12,000 model runs = 19%), we wondered if different variables contributed to reaching the top 5% best outcomes. We therefore performed another PRIM analysis, but this time we selected only model outcomes that resulted in a market share > 0.603. This resulted in PRIM identifying four variables that significantly contributed to highly desirable outcomes, with a coverage of 80% and a density of 98% (see Table 6.2B). These variables are a low consumer preference towards banks' sustainable operations and a moderate to high preference towards bank's digital services, besides the variables that were previously identified.

Highly undesirable outcomes cannot be attributed to specific variables

Next, we also wondered if there were variables that significantly contributed to very undesirable scenarios. As such, we conducted a PRIM analysis on the outcomes with a market share < 0.595. Interestingly, PRIM did not identify any specific variable that significantly contributed to these outcomes, indicating that these outcomes emerge from a wide range of very specific combinations of uncertain variables. Indeed, when checking the parameter values of these scenarios, we observed larger differences between the best three scenarios and the worst three scenarios (see Table B.5).

6.4 Exploring special scenarios with shock events

Per the suggestion of Expert 2, we modeled a shock event in which a sizeable scale challenger bank (with 4M customers at t=0, which is c.4% market share) fails, leading to all its customers suddenly having to switch their PCA provider. The simulation time step of this shock event was stochastically determined.

A shock event step-increases the PCA market share of big 4 banks but does not change the observed dynamics

We observed that the presence of a shock event indeed increased the market share by about 2%, however, the observed dynamics were similar as during normal conditions (i.e., same variance between worst and best case scenario). Using PRIM (coverage 74%, density 93%), we again found that the PCA market growth and consumer preference towards sustainability, digital, and service contributed to desirable model outcomes (market share > 0.624), although their significance ranges were bigger relative to the previous observations (see Table 6.2C). In addition, and as expected, the presence of a shock event was found to be significant towards the desirable outcomes, although interestingly the timing of the shock event did not matter (as indicated by the very large significance interval relative to the entire uncertainty interval). This latter finding dictated that while the jumps in market share (i.e., the "vertical" lines) did seem longer at the beginning of the simulation time, this was just an optical illusion.

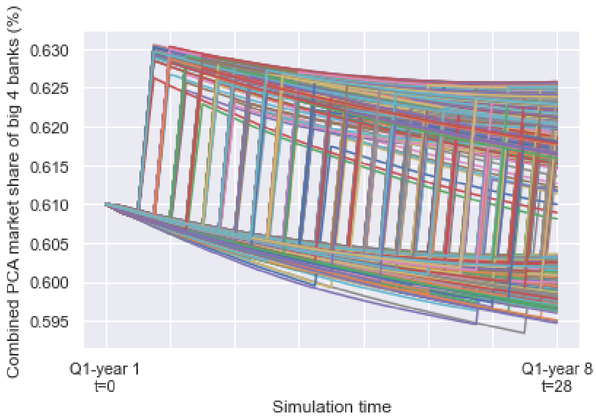


FIGURE 6.4: CA market share dynamics of the big 4 banks as generated by the open explorations of 400 scenarios with 30 repetitions each in case of a shock event.

Chapter 7

Model verification and validation

In this chapter, we describe the actions that were taken to ensure that the model met the design requirements and is thus fit-for-purpose (Van Dam et al., 2012). This was done through both model verification and validation. We conducted the former to ensure that we correctly translated the conceptual model into the simulation model, i.e., that the model is operating as expected, and we conducted the latter to ensure that the simulation model produced sufficiently accurate behavior in conformance with the real-world for the intended application of the model, i.e., that the model is fit for purpose (Sargent, 2010). Given the novelty of our modelling approach, however, we first set verification and validation requirements in section 7.1. The verification process is consequently described in section 7.2, and validation is addressed in section 7.3. This chapter thereby answers SQ6.

7.1 Verification and validation requirements

Given the novelty of our modelling approach, in which we combined game theory concepts with ABM and EMA, there was no guide to the verification or validation process. Instead, we researched verification and validation techniques for each of the modelling approaches and selected the ones that could be applied to our model. We also included some validation tests that are usually performed for System Dynamics models, as these tests are generally recognized for their purpose (Senge and Forrester, 1980). Finally, we also briefly compare how our approach to verification and validation relates to those for existing (statistical) market share models.

First, to the best of our knowledge, there is no literature available on how game theory models should be verified or validated. Instead, game theory is sometimes applied as a method to validate another model (Bigi et al., 2015; Zhang et al., 2010). There are some scholars that submit their model to a controlled laboratory test to examine to what extent the actual behavior of economic agents conforms to the game-theoretic predictions (Amaldoss and Jain, 2002). This latter approach to validation is, however, impractical to apply to our model as we would need to perform thousands of laboratory tests - one for each of the 12,000 plausible future scenarios that we modeled.

Second, the general approaches to verification and validation of agent-based models are described in detail by Van Dam et al. (2012). Heckbert et al. (2010), however, demonstrated that agent-based models that address ecological economic often lack empirical calibration and validation. They found that *"model outputs rest on weak theoretical representations of human decision-making; empirical data is absent often because data is collected and available only at a coarse resolution, and key model functions may be deeply buried in lengthy code requiring great skill to develop and debug"*. Indeed, model development issues aside, multiple researchers have concluded that validating models of complex systems with their nefarious feedbacks poses unique challenges (Grimm et al., 2006; Janssen, 2002; Lux and Zwinkels, 2018). The latter can be attributed to the complex nature of ABMs and its irreducible emergent properties at a system level. In response, (Heckbert et al., 2010) concluded that many modelers do not attempt empirical validation, but instead go for a "proof of concept". It was found, however, that most validation problems originate in the calibration of the model. This calibration often entails using full parameter ranges for sets of initial conditions, and discarding parameter sets that do not yield outcomes which match empirical realizations. We, however, advantageously turned to EMA, in which the problem of calibration is less significant as we embraced the uncertainties. In fact, EMA seems to partly overlap with sensitivity analysis, which is often conducted to understand the sensitivity in the model output when certain input model parameters are changed and to check if altered input parameters could cause the model to fail a previously passed test (Senge and Forrester, 1980). In all, we therefore found that multiple standard tests from the ABM field could be performed for verification and validation, but that our approach of EMA helps significantly with the design of a model that is fit for purpose.

Given the selected approach to verification and validation as concluded above, it was interesting to observe that other existing market share models are usually validated to a much lesser extent. Given that existing models rely on historical time series data, they are usually assessed in terms of statistical accuracy as well as practicality (Charan, 2020). Metrics/tests that help assess the goodness-of-fit and the reliability of the model include: Adjusted R^2, estimated standard error, and holdout tests. The latter test entails using the estimated model coefficients to predict the shares for a further 8 to 12 weeks. This prediction is then compared with the actual share data of those weeks to assess the quality of the model. As our model does not rely on historical data, we could not use these kinds of statistical tests.

7.2 Model verification

According to (Van Dam et al., 2012), agent-based models are verified in multiple consecutive and iterative steps. It first includes verifying that the variables of a single agent have been modeled correctly, after which the agent's behavior is verified. Next, the interactions between agents and the emergent behavior of multiple agents are examined. Also note that the verification was performed before the experimentation, but is only reported upon here.

7.2.1 Tracking agent behavior and single-agent testing

To verify the model operation at the level of the agent, we first monitored several relevant outputs of the individual agent behavior. We specifically monitored the input, state, and output of each of the internal processes of individual agents. This included the number of customers per bank, and whether and when banks decided to adopt a sustainable business model. Doing so allowed to observe all the "thought" processes internal to an agent, and confirmed that agents were indeed making decisions to become sustainable based on observations that they made about the system or the self. As such, it was verified that agents move from an active state to a latent state through the implementation state.

We furthermore verified that we correctly modeled several variables by simulating the model multiple times with different random seeds. This included checking if (i) random generators correctly produced different numbers, (ii) the dynamic feature scores always had a value between 0 and 1 throughout the simulation, (iii) that the price feature had stochastic fluctuations, and (iv) the digital feature scores became closer together throughout the simulation, which indeed slowly converged to values in the upper range (e.g., between 0.9 and 1). During these checks, we identified some coding implementation errors which were resolved.

7.2.2 Interaction and multi-agent testing

To verify a correct operation at the level of the system - where any emergent behaviors will most likely be visible - we confirmed whether the observed changes in model variables originated from the correct entity/interactions (Van Dam et al., 2012). To this end, we used *theoretical prediction and sanity checks* to test explicit predictions from the conceptual model and the model narrative about how a typical agent theoretically will behave under normal operating inputs. That is, we checked whether the sustainable banking implementation strategies were functioning as expected. For example, we confirmed that an agent with the 'threshold' implementation strategy became sustainable if its market share fell below its predetermined threshold. Overall, we did not find any deviations from the theoretical predictions, which suggested that there were no implementation errors.

After we found the agents to behave as expected under normal inputs, we used *extreme conditions tests* to 'break the agent' and evaluate if the agent behavior remained plausible in these cases. Variables that were included in the extreme conditions tests can be found in Table 7.1. Note that these extreme values are values outside the uncertainty ranges as explored in the model. (Van Dam et al., 2012). We found all agent variables to display plausible behavior during the extreme conditions. For instance, banks did not get a negative amount of customers when the extreme condition was a PCA market growth of 1.7, which entails a shrinking market. Nevertheless, we implemented a check for agents to raise an error if they reach zero customers because we had to ensure that this behavior could not be generated during the later simulations.

TABLE 7.1: Model variables included in extreme condition test for model validation.

Variable name	Low extreme value	Normal value	High extreme value
PCA per capita	1.7	2.1	2.7
Quarterly switching volume	0.2 million	1 million	40 million

7.3 Model validation

As the purpose of our model is to explore plausible future states, validation could not be established by simply comparing computed behavior to "real" system behavior (Van Dam et al., 2012). Instead, the validation of our model focused on whether the model is useful and convincing in its explanation of how a system possibly operates or as to what the plausible states of the system may entail. As such, we modeled each validation test with 25 scenarios that were each executed with 5 repetitions.

7.3.1 Boundary adequacy test

To test if the model boundaries and implemented aggregation levels match the purpose of the model, we performed a boundary adequacy test (Barlas, 1989; Qudrat-Ullah and Seong, 2010).

Bank features for aggregated consumer choice of bank behavior are valid but might introduce numerical inaccuracy

The research conducted in this study has aggregated consumer choice of bank behavior into a few bank features, and thus left the effects of different factors that influence consumer behavior out of scope. There are two processes, however, that could have considerable influence on the consumer choice of bank. First, according to (Accenture, 2020), there may be some upper limit on how many people will potentially choose a digital challenger bank. We did not implement such a limit per type of bank (traditional bank, online banks, or building society) as the data on this matter is insufficient, but this could have compromised the numerical validity of the model. Second, there are significant differences in consumer behavior between selecting a first and secondary bank. Devlin and Gerrard (2005), for instance, showed that both recommendations from others and offering a monetary incentive are significantly more important in prompting the choice of a secondary bank. As the current PCA per capita is close to 2, however, we expected that these differences in the consumer choice of bank behavior currently level out and therefore argue that the aggregated consumer choice of bank behavior in bank features was valid. Finally, we also did not consider the cross-market influences on consumer choice of bank behavior that originates in their experiences with a savings account or another product at their current account provider (Vinayak, 2009). This is because we expected these influences to be negligible (Accenture, 2020), besides them also being out of the scope of this research.

Exogenous modeled variables are sufficient to reach the goal of the model

Considering the aggregation level and boundary of the model, we based the level of detail on the function of the model: showing the potential dynamics in the PCA market shares among the UK retail banks. Towards this goal, we modeled some variables exogenously. Most importantly, we modeled the customer switching volumes and PCA market growth with a level of detail that highlights the total volume only, instead of going into more detail on how these volumes came to be based on individual consumer behavior and market developments. To accurately include the latter, we would need different sub-models on these dependencies, which would have been possible if there was data available on how consumer behavior results in particular quantities of market growth and switching volumes. This data, however, was not available and time constraints prevented us from generating this data ourselves. Similarly, we modeled the scaling of both the digital and price feature score exogenously. This is because these processes were out of scope of the model, and including them in more detail would require different studies and also the design of sub-models. For reaching the goal of this research, however, we considered the aggregation level and the set boundary of the model sufficient as it allowed to gain insights into our defined problem with its chosen framing (Walker et al., 2003).

7.3.2 Structure-oriented behavior test

To validate that the model structure conformed to the suggested behavior by literature, we performed a structure-oriented behavior test. This test validates the model structure indirectly by discussing model-generated behavior patterns in light of certain behavior tests, such as the extreme conditions test (see Table 7.1) and structure tests. These latter tests compare the model output of different model structures.

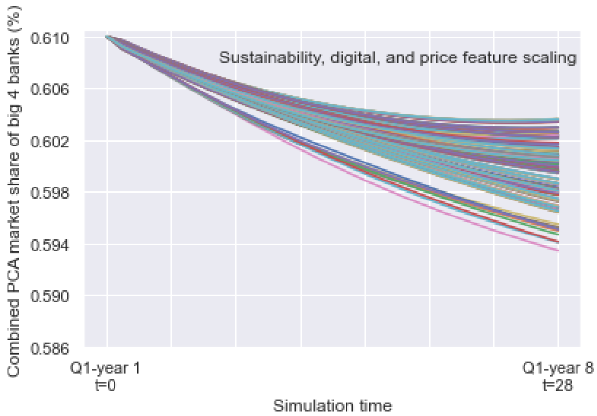
The dynamics of bank features cannot be modeled in isolation

After we validated the aggregation level of the exogenous modeling of bank feature dynamics, we had to validate that they were implemented in a manner that produces behavior conform to the real-world. To this end, we simulated the model with and without these exogenous dynamics (i.e., digital and price feature scaling), as well as with and without the endogenous decision-making of banks (i.e., sustainability feature scaling). We modeled this by manually turning on and off the model structures that are responsible for these scaling operations. As such, no feature scaling entailed that banks' initial feature value was constant throughout the simulation. On the other hand, the phrase 'baseline' indicates the model output with functional sustainability, digital, and price feature scaling. In turn, the 'best case scenario' refers to the upper limit of the market share outcomes, and the 'worst case scenario' refers to the lower limit.

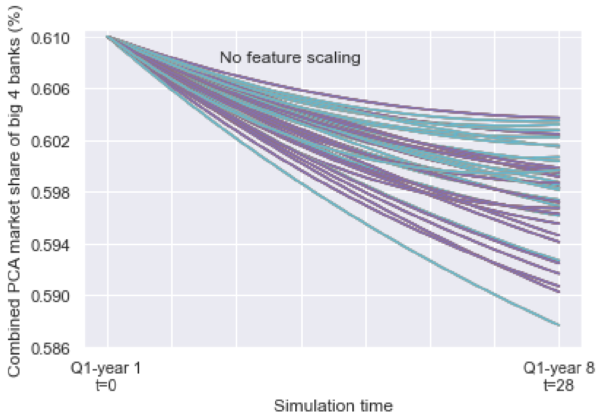
We observed differences in the model output between the baseline and when there is no feature scaling, with the latter being characterized by a higher variance bounded by a similar best case scenario and a more undesirable worst case scenario (c.0.5% worse) (see Figure 7.1a and 7.1b). In addition, no feature scaling resulted in a lower coverage of the variance interval, i.e., multiple scenarios resulted in the same model outcomes. This latter observation can be explained by sustainability, digital, and price feature scaling all being modeled with stochastic dependencies, and as such, there will be different outcomes for different repetitions if feature scaling is active. The decrease in variance in the baseline, in turn, was also conform to the expectations, as the strategical decision-making of bank managers (whether modeled endogenously or exogenous) aims to increase their attractiveness (Accenture, 2021; Charan, 2020). As such, we expected the decrease in market share to be of smaller magnitude if the big 4 banks improved their attractiveness, although the magnitude remained dependent on the competitive environment. That is, if all the banks in the system improved their attractiveness, they potentially became more attractive than the big 4 banks. this latter line of reasoning might explain the observation that the best case scenario did not improve when big 4 banks made strategical decisions.

We furthermore observed that having only sustainable feature scaling resulted in more undesirable worst case scenarios relative to having no feature scaling, but that multiple scenarios also outperformed the latter's best case scenario (see Figure 7.1b and 7.1c). On the other hand, having only digital feature scaling resulted in similar model outcomes as having no feature scaling (see Figure 7.1e and 7.1b). We furthermore observed that only price scaling resulted in a similar best case scenario as the baseline, but with a better worst case scenario, thereby effectively decreasing the variance in the model outcomes (see Figure 7.1d and 7.1a). This latter observation also applied to the case in which there was only digital and price scaling (see Figure 7.1f). Interestingly, we observed that the little effectiveness of standalone digital scaling or in combination with price feature scaling disappeared when we combined digital scaling with sustainability scaling. That is, we observed that sustainability and digital scaling resulted in smaller variance than only sustainability scaling, resulting from a similar best case scenario and a better worst case scenario (see Figure 7.1g and Figure 7.1c). Having only sustainability and price scaling, in turn, resulted in model outcomes that were similar to having only price scaling (with some outlier scenarios) (see Figure 7.1h and Figure 7.1d). These latter two observations clearly demonstrate that the effects of strategical decisions (whether modeled endogenous or exogenous through bank feature dynamics) cannot be studies in isolation, as there are interdependencies in their effectiveness. This is in conformance with literature that suggests the factors influencing consumer choice of bank behavior interact synergistically, (mutually) destructive, or not at all (Charan, 2020; Payments Authority, 2022).

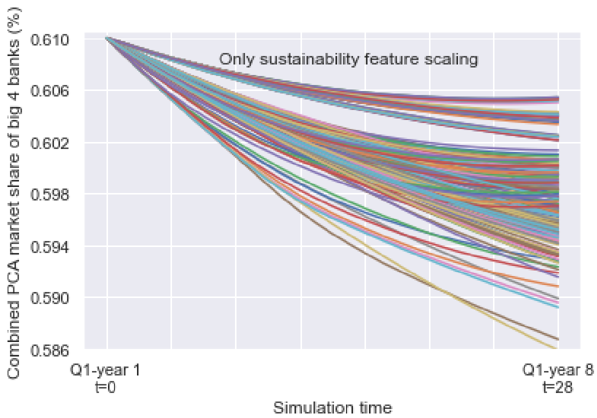
We furthermore have the following explanations of the observations in light of the model structure. First, the consistent limited effect of the digital feature scaling on model outcomes could be the consequence of the convergence of the bank features, resulting in little differences in the relative attractiveness of banks. That is, throughout the simulation, the banks with the best digital feature remained at the top, whereas the banks with the worst digital feature improved their feature score while still remaining the worst. This matches the expected convergence between banks' digital capabilities and the expectation that digital challenger banks will remain the best digital service providers (FCA, 2022a). Second, the ability of price feature scaling to consistently decrease the variance between the worst and best case scenarios could be explained by the stochastic nature of the price feature scaling. That is, if there is price scaling, there is the possibility that consumers that would normally choose a bank for its sustainable or digital performance are attracted to price instead. In turn, if there is no price feature scaling, the sustainable, digital, and service features have a larger influence on the changes in market share. These latter features apparently facilitate dynamics in market share (either resulting in more desirable or undesirable scenarios) in certain scenarios. As such, monetary incentives seemed to be effectively compensating for the lacking bank performance on the other bank features when attracting customers, which is a finding in accordance with literature (FCA, 2022a; MoneySavingExpert, 2022). This effect works towards all the banks in the simulation, which explains why in some scenarios with feature scaling the big 4 banks might be the most attractive (and hence result in desirable outcomes), whereas in other scenarios different banks from other bank categories are more attractive (and hence resulting in undesirable outcomes).



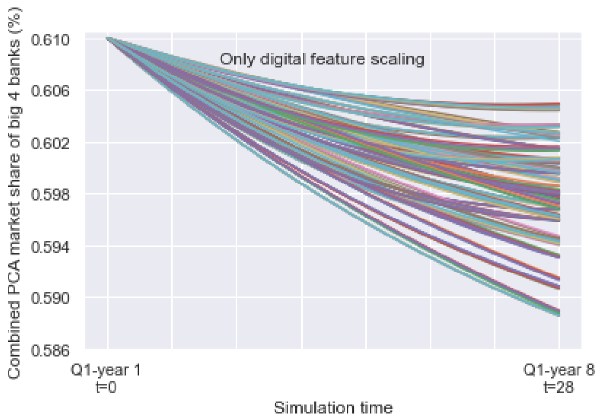
(A) Baseline.



(B) No sustainability, digital, and price feature scaling.

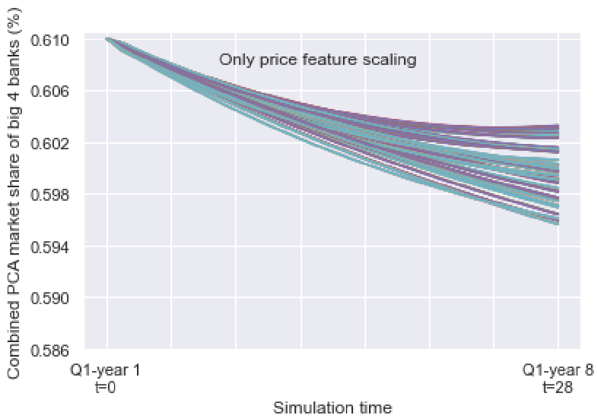


(C) No digital and price feature scaling.

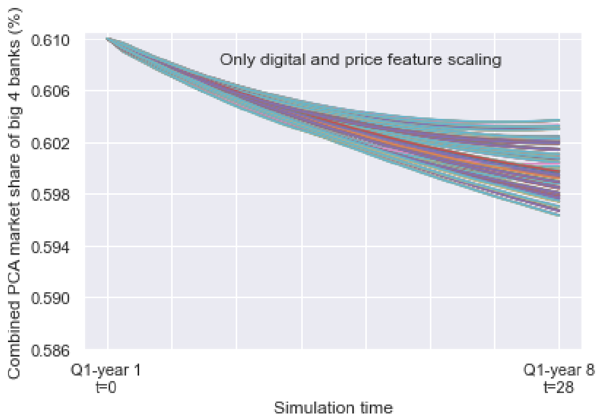


(D) No sustainability and price feature scaling.

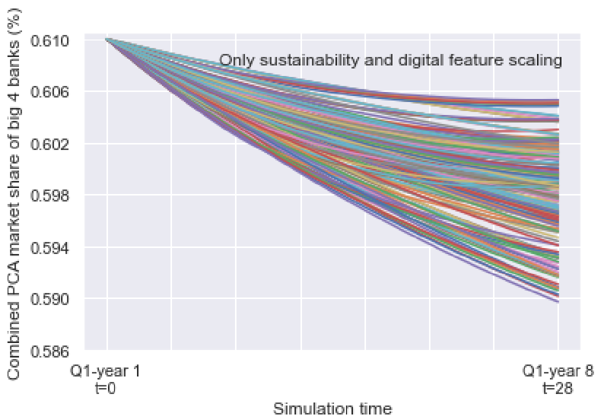
FIGURE 7.1: Comparison of model results under (A) normal conditions, i.e., sustainable, digital, and price feature scaling, (B) without any feature scaling (so input features have constant values throughout the simulation), (c) with only sustainability scaling, (D) with only digital scaling, (E) with only price scaling, (F) with only price and digital scaling, (G) with only sustainability and price scaling, and (H) with only sustainability and digital scaling.



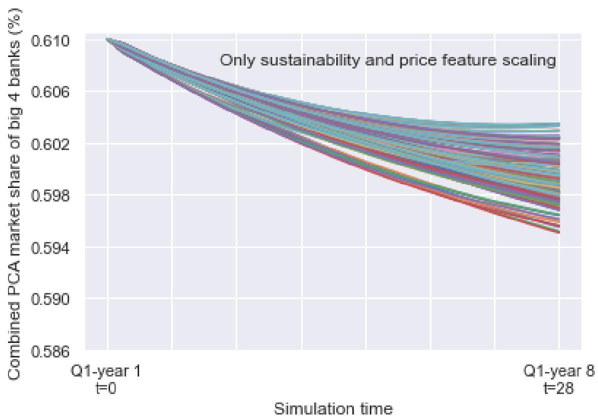
(E) No sustainability and digital feature scaling.



(F) No sustainability feature scaling.



(G) No price feature scaling.



(H) No digital feature scaling.

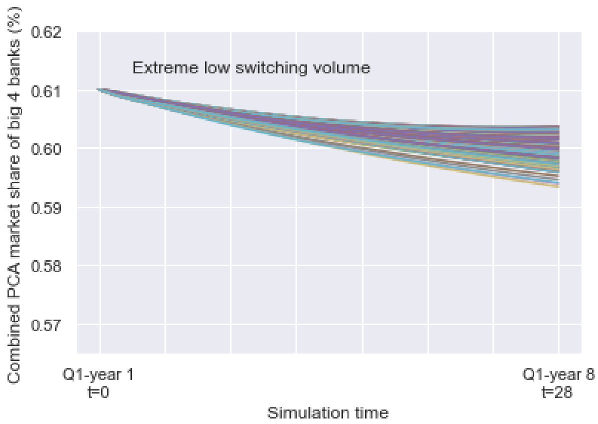
FIGURE 7.1: Comparison of model results under (A) normal conditions, i.e., sustainable, digital, and price feature scaling, (B) without any feature scaling (so input features have constant values throughout the simulation), (c) with only sustainability scaling, (D) with only digital scaling, (E) with only price scaling, (F) with only price and digital scaling, (G) with only sustainability and price scaling, and (H) with only sustainability and digital scaling.

Extreme conditions confirm that model outcomes are sensitive to the PCA market growth

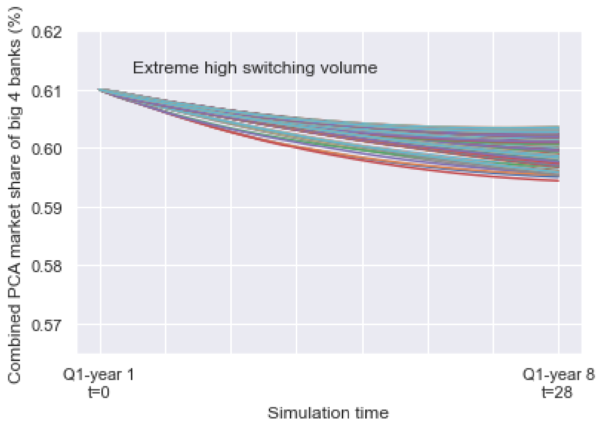
Next to running the extreme conditions tests for verification purposes, we also evaluated if the generated model behavior remained plausible under the extreme conditions. We observed that the model was behaviorally sensitive but not numerically sensitive to the extreme conditions of the switching volume (see Figure 7.2a and 7.2b compared to Figure 7.1a; Please note the different scales in the y-axis). This may be explained by the inclusion of consumer switching volumes in both the customer attrition and acquisition payoff function. As such, the magnitude of the switching volume cancels out during the process of customer attrition and acquisition. This might be caused by the mathematical operation to inverse the bank feature scores for calculating the attrition score relative to acquisition score, meaning that the only difference between the scores is the consequence of the bank feature weights that are multiplied with the bank features. While our model structure as such might lead to the underestimation of the effects of switching volumes on market share dynamics, it could also be that this result is conform to the real world. Historical reports support this latter explanation, as they generally also conclude that the competitive differentiation between UK retail banks is simply too small for switching volumes to effectively change market shares (Revealing Reality, 2017; SMF, 2018).

Regarding the extreme conditions for PCA market growth, we observed that the model output was both numerically and behaviorally sensitive to the extreme conditions of PCA market growth (see Figure 7.2c and 7.2d). Nevertheless, the generated model behavior remained plausible. Interestingly, the variance in model output consequent to different scenarios was almost absent in the case of extremely low market growth, whereas the variance in the case of extreme high PCA growth there still was variation of similar magnitude as in the baseline. This observation might be explained as follows. In the extreme conditions test, we kept the PCA market growth constant while varying other model uncertainties. As such, the extremely high growth magnified the relatively small influences of banks' strategic decisions and other uncertain model variables such as the switching volumes, thus eventually leading to significant variation in model outcomes.

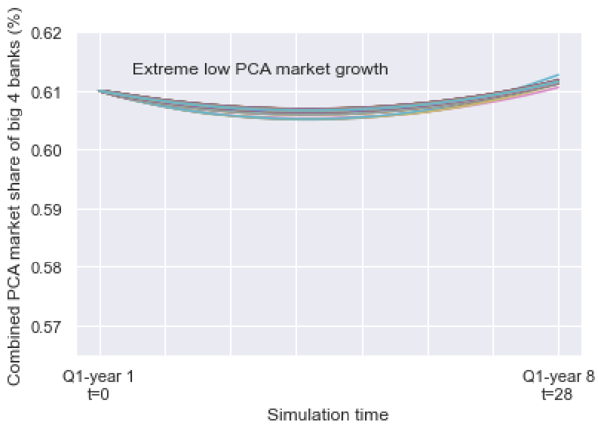
Overall, the extreme conditions confirmed the results of the PRIM scenario discovery analysis that the variance in the generated model behavior depended heavily on the exogenous modeled PCA market growth. This can be explained by the endogenously modeled payoff functions being dependent on the exogenous modeled PCA market growth, thereby limiting the range of behavior that could possibly be generated. Given the intended exploratory purpose of this study, this limited model behavior hampers the discovery of extremely unexpected market share dynamics. Nevertheless, the model does provide insights concerning the normal behavior of the system and is in line with the report of the (FCA, 2022a) that the PCA market growth is the main driver of market share dynamics in the UK retail banking industry. The extreme conditions thus validated the model, as it responded in a completely appropriate and logical way to the extremities.



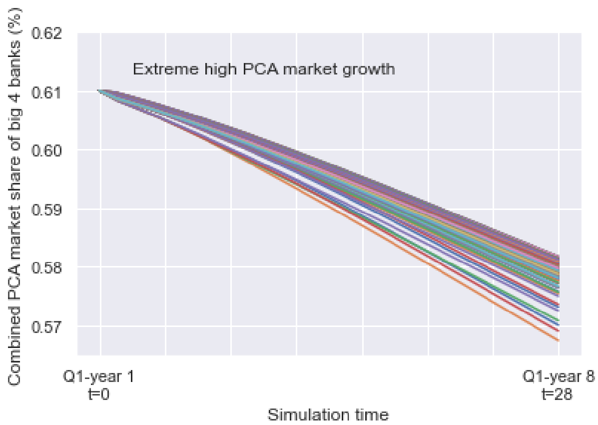
(A) Extreme high quarterly switching volume.



(B) Extreme low quarterly switching volume.



(C) Extreme low PCA market growth



(D) Extreme high PCA market growth

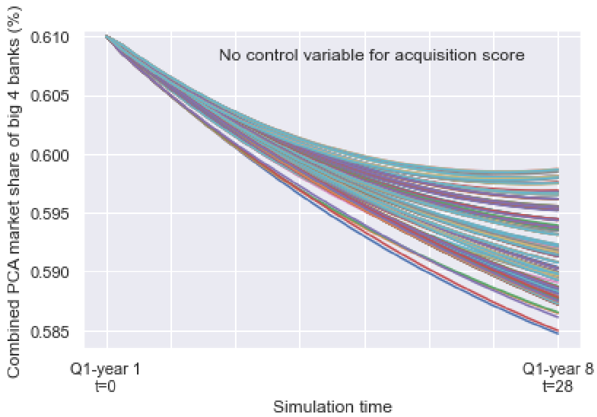
FIGURE 7.2: Comparison of model results under (A) extreme low PCA market growth, (B) extreme high PCA market growth, (C) extreme low switching volumes, and (D) extreme high switching volumes.

Bank features are the main driver of the observed behavior and the control variables are the main driver of the numerical results

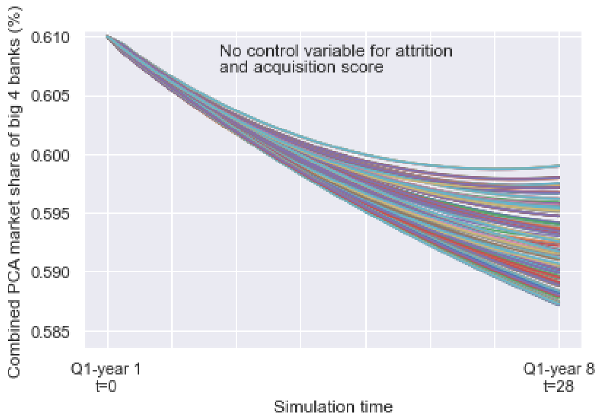
Finally, to validate the used control variables, we simulated the model with and without them. We observed that no control variable on the attrition score slightly increased the variance between the best and worst case scenario due to a worse worst case scenario. On the other hand, not including a control variable on customer acquisition did numerically influence the model results. We observed that both the best and worst case scenario resulted in a bigger decrease in the market share of the big 4 firms, and the variance between these scenarios also increased. These observations contract each other, as the former was against our expectations and the latter supports it. That is, we hypothesized that without a control variable a similar attrition score for a mid-tier firm and a big 4 firm would result in disproportional customer attrition, i.e., it would lead to very little customer attrition by the big 4 banks. While theoretically, our hypothesis still holds – as partially supported by the observation that that not including a control variable on the acquisition score would result in too little customer acquisition by the larger firms – we expect that the limited influence of the attrition control variable originates in the smaller banks already having low attrition scores to begin with, so there is little need to correct them.

(A) Baseline.

(B) No control variable for the attrition score.



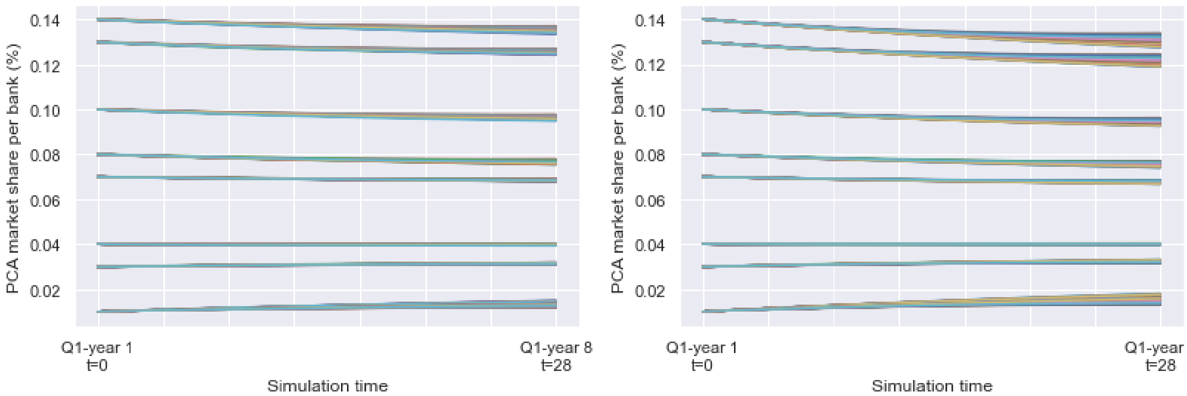
(C) No control variable for the acquisition score.



(D) No control variable for both the attrition and acquisition score

Figure 7.3: Comparison of model results under (A) normal conditions, i.e., with control variables for the attrition and acquisition score, (B) without a control variable on the attrition score, (C) without a control variable on the acquisition score (D) without a control variable for both the attrition and acquisition score.

We found further evidence for the validity of the control variables when we observed during the exploration of the model results that smaller subsidiaries increased in market share whereas larger ones decreased. As this observation correlated with bank size, we suspected that the control variables may, after all, have an unintended effect resulting in these observations. If we turned off the control variables, however, we observed the same trends in the dynamics (see Figure 7.4). This indicates that the bank features are the main driver of the observed behavior, and that the control variables are the main driver of the numerical results. For this research, we thus considered the presence of control variables valid, although we acknowledge that there is a low level of detail on the precise mechanisms.



(A) Baseline.

(B) No control variable for the attrition and acquisition score.

FIGURE 7.4: Comparison of model results under (A) normal conditions and (B) without a control variable for both the attrition and acquisition score.

7.3.3 Literature comparison

As our model aimed to explore future states while considering a strategic innovation, historical replay was not possible. Nevertheless, we based the model's initial conditions and structure on real data. As such, we could claim an increase in model validity by elements of our model (such as initial values) being compatible with an available theory or published case studies (Van Dam et al., 2012). We do note that these opportunities for validation were sparse, as models (both agent and non-agent-based) of the same or similar systems problems did not exist (Xu et al., 2003). In addition, the above structure-behavior test also already discussed the validity of the model structure conform the real-world through literature comparisons.

Parameter-confirmation test

We conducted a theoretical parameter validation test to confirm that we modeled the model variables in conformity with the real-world system and laws of nature (Pruyt, 2013). First, we estimated some variables based on literature, and we extensively documented this process as part of the research (see appendix B.1). For instance, we estimated the market shares based on the synthesis of multiple sources. Second, we were not able to confirm some parameters due to lacking data on these matters. Hence, we based their values on the modeler's own assumptions. For instance, for the contribution of each bank feature to customer attrition, we assumed equal contributions by the sustainable, digital, and price features. As we explored the uncertainties of a large part of these estimated variables during EMA, we argue that possible inaccuracy in their estimations does not compromise the validity of this model.

Behavior reproduction test

Next, we aimed to generate output validity by a behavioral reproduction test (Qudrat-Ullah and Seong, 2010). This test evaluates if the model-generated behavior is in line with the observed historical behavior of the real-world system (Schwaninger and Grösser, 2020; Sterman, 2000). Ideally, the model should be tested to behavior both from stable periods in the real-world system and to unstable periods. The data on market shares from before the digitalization transition is, however, largely not available and of low quality due to many acquisitions, and this limits the behavior reproduction test. We furthermore note that the behavioral reproduction could only be done at a low resolution, as (i) we compare future predicted behavior to historical data which dictates caution in claiming increased validity, and (ii) we could only compare market share dynamics per bank category, as no historical data is available on the resolution of the number of customers per bank.

We found that our model generated less change in market share of big 4 banks (1-2% over coming 7 years) compared to the dynamics in market share due to the digitalization transition (3% decrease in the past 4 years) (FCA, 2022a). While we cannot comment on these numerical differences as future quantities cannot reliably be compared with historical quantities, both our results and the historical data demonstrated the same behavior, being a gradual change in market share. The model behavior thus corresponded to what might be expected of the real-world system.

We note that an additional validation test could be to actually replicate the digitalization transition with our model and compare it to the historical data mentioned above. This would require historical data on consumer choice of bank behavior, proxies for the bank features, PCA market growth, switching volumes, and market shares per bank. All this data is likely available, but time constraints prevented us from performing this validation test.

7.3.4 Model evaluation by expert Panel

Given all the difficulties with validating ABM models that concern ecological economics, Moss (2008) argues that "volatile," and "soft" calibration with stakeholder knowledge is perhaps the best strategy. The problem with this approach is that if different stakeholders have different subjective understandings of the system, the model might be an accurate representation of some views but an inaccurate (though precise) representation of others. As such, we organized a feedback panel session in which we asked five experts to validate the model structure and outcome. The credentials of these experts are reported in Appendix A.

Model structure captures all relevant components concerning market share dynamics

The experts indicated that the model included all the relevant components concerning market share dynamics. This specifically included the selected bank features and their associated weights, and that the model assumption that these weight differencing towards attrition and acquisition are sufficient to gain insights into these processes. The experts also recognized the importance of the control variables. Regarding the strategical decision-making of the banks, the experts confirmed that the exogenous trends of digital competence convergence and stochastic price fluctuations are inherent to the system under study, and should thus be included. Finally, the experts validated our claim that there is insufficient knowledge on consumer behavior to model an endogenous rise of switching volume / market growth based on the attrition and acquisition score. The experts thus perceived the exogenous modeling of multiple variables as valid.

Interestingly, as we presented the experts with the model assumptions and underlying mechanisms, they also immediately recognized the limitations of the model and identified aspects that would need to be added. This for example included the control variable for the acquisition score: the so-called PROMO score. The experts validated that this control variable helps with establishing some numerical accuracy, but also argued that the variable is not sufficient in representing marketing efforts. However, the expert panel did also not have any suggestions on which control variable might need to be added or used instead, thereby explicitly recognizing the lack of knowledge of drivers of consumer choice behavior.

Model output is very plausible but numerical accuracy needs further reseach

The experts clearly recognized the model output as very plausible behavior given the market share trends that they have encountered in their work-life. They stated that "we would be more concerned about the validity of your model if you showed us a 5% difference in market share in the coming seven years". Nevertheless, they were at first surprised that the impact of different strategies to the adoption of a sustainable business model (i.e., being a leader or follower) did not have a significant impact on the resulting market share, but they agreed that this is plausible behavior.

One bigger point of controversy was the gain in market share by mid-tier banks. This outcome is not what the experts expected based on their experience. After some discussion among the panel, we eventually found two explanations: (i) mid-tier banks are currently not capturing their full potential, meaning that they face some barriers that prevent them from gaining the market share that they are predicted to gain based on our simulation, or (ii) the simulation model is inaccurate and some control variable is missing. Only further validation with UK retail bank experts and interviews with mid-tier bank managers could shed light on this point.

With regard to the first point, i.e., that the model may be numerically inaccurate, the expert panel expressed the importance of considering different age groups and banking personalities. That is, they for instance expected that the digital challengers will continue to gain market share as tech-savy youngsters are growing up and likely to choose this type of bank. In addition, there might be some upper limit to the amount of people that considers choosing a mid-tier bank. Customer characteristics could thus have a potentially large impact on the model outcomes. Nevertheless, the expert panel agreed that this should be included in future research and that the model is valid for its exploratory goal.

Finally, the experts also perceived the low computational demand as well as the need for no time-series historical data as a major advantage of our methodology. As this model has, in part, been designed as a proof of principle model, we met the aims of the model structure validation via expert validation when the experts expressed that such a model would indeed be valuable to them.

Nevertheless, we must note that during the panel discussion, it became clear that some experts were familiar with statistical modeling methods for market share dynamics and were as such biased by this knowledge. On expert, for instance, kept mentioning that the underlying distribution of bank feature scores may turn the model results invalid if this distribution is very skewed. While this may indeed be the case for statistical modeling methods, we argue that our agent-based model is not limited by such distributions.

Bank feature scores may explain most of the observations

When trying to explain the model outputs, the bank managers generally reasoned from the initial bank feature scores. For instance, that the consumer choice of bank behavior towards service should not be very low (i.e., weight < 0.18) to result in desirable outcomes (market share > 0.602), was explained by the big 4 feature scores on the sustainability, digital, and price feature generally being higher than the feature score on service (see Figure 7.5). Specifically, if there was little consumer preference towards service quality, it meant that the other three features are automatically more valued and would result in a higher attractivity for banks (as their attrition score would be lower, and their acquisition score higher), and, thereby, more desirable outcomes. The experts thus validated our previous conclusion that the bank features are determining the behavior in the dynamics of the customer market shares of banks.

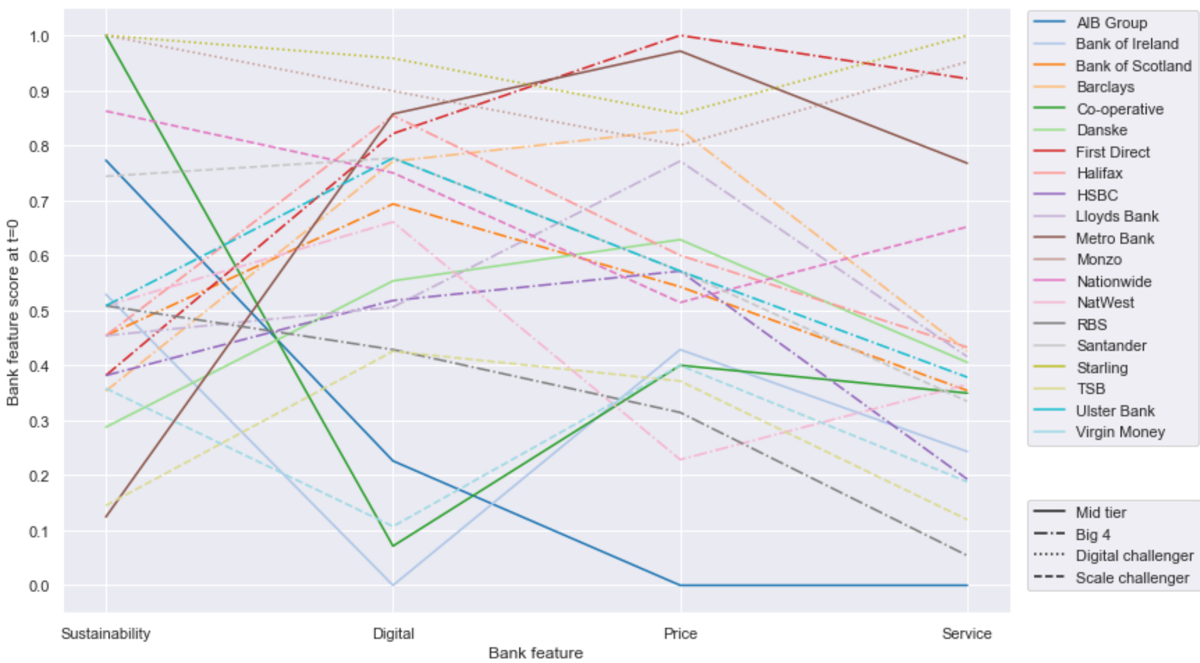


Figure 7.5: Initial bank feature scores per bank (indicated by color) with a label of its bank category (linestyle). Note that this figure only displays the price feature score that results from one of the two price proxies - the one based on a consumer survey - as the other proxy is a stochastic monetary switching incentive that inaccurately represents a bank's performance on the price feature if captured at a static moment such as t=0.

7.4 Conclusion

We performed various verification and validation tests to assess whether the model could be considered useful for the objective of this research (Senge and Forrester, 1980; Sterman, 2000). This objective is exploratory in nature, as we aim to gain insight into the range of dynamics in the PCA market shares and investigate the role of strategical decisions towards the adoption of a sustainable business model in these dynamics. We do note that our validation process was very different from the statistical tests that are usually performed to validate the existing types of market share models. Instead, we used methods that are commonly used to validate ABM models, and as such, we have collected compelling evidence that our the model is useful and convincing in its explanation of how the market share dynamics of UK retail banks possibly operate or as to what the plausible states of this system may entail.

First, we demonstrated that model boundaries and implemented aggregation levels match the purpose of the model but could be the source of numerical accuracy. As such, future insights into consumer behavior towards the bank features, types of banks, and primary vs. secondary account differences may turn the use of merely four bank features invalid. Second, we demonstrated the effects of strategical decisions (whether modeled endogenous or exogenous through bank feature dynamics) cannot be studies in isolation, as there are interdependencies in their effectiveness. Third, we observed that the PCA market growth is the dominant driver of the model outcomes due to the payoff functions being modeled based on this exogenous variable. Given the intended exploratory purpose of this study, this limits the behaviors that can be observed from model outputs and thus makes it hard to uncover extremely undesirable system evolution. Nevertheless, multiple structure-behavior tests showed an appropriate model structure according to the real-world system, and we thus did not consider the numerical inaccuracy as a limitation for this exploratory study. Fourth, we performed an expert validation. Specifically, we used the expert discussions to provide us with insight into which aspects and outcomes are sufficient and which need extra work to provide a useful model to the problem owner, i.e., bank managers and regulators. As all these four sources of validation consistently concluded that the model structure was valid and that the model outcomes were plausible, we concluded that the model was fit for purpose, thereby answering SQ6 (Van Dam et al., 2012).

Chapter 8

Discussion and conclusions

In this final chapter, we present the conclusions that can be drawn from this study. To this end, we first discuss the findings that were made during this study in section 8.1. In section 8.2, in turn, we discuss the theoretical implications of this study. In section 8.3, in turn, we translated the insights gained from the model into practical policy recommendations for bank managers and regulators. Next, in section 8.4, we explicitly state model limitations and assumptions to prevent future inadequate use of the model (outcomes). In addition, we also present future work that could address these limitations. Finally, in section 8.5 we present the conclusions of this thesis. This chapter thereby answers the main research question on what the effect in the customer market share of UK retail banks is when they adopt sustainable business models given their competitive environment.

8.1 Discussion

Here, we will discuss the findings that we made regarding (i) the complexity of the modeling activity in this study (i.e., the methodological question of this thesis), and (ii) the UK retail banking industry and the simulated future dynamics in its customer market shares (i.e., the theoretical question of this thesis).

8.1.1 Discussion of the model design

In this study, we designed and applied an agent-based customer market share dynamics model. In short, the model operated as follows. Based on the language of game theory, the model employed a framework for strategic interaction in which customers (i.e., a utility) were redistributed among the banks according to a payoff function. Specifically, two separate payoff functions determined the customer attrition and acquisition per bank per simulation time step. To this end, the payoff function calculated the relative attractiveness of a bank compared to its competitors and multiplied this relative attractiveness with the exogenously determined switching volume and PCA market growth. The relative attractiveness, in turn, was determined based on weighted bank features (i.e., bank characteristics such as digital capability and service quality) that represented the consumer choice of bank behavior. The parameter values of these bank features, however, depended on time. That is, they were determined by the endogenous decisions of banks on whether to adopt a sustainable business model, besides being influenced by exogenous system variables such as stochastic monetary incentives and increased digital competences among all the banks. By implication, as the bank features depended on time, the payoff function was adaptive to the evolving state of the system. Finally, to model the endogenous decision-making of the banks, we designed six innovation implementation strategies that dictated their behavior, where "implementation" refers to being an e.g., leader or follower.

This specific model design renders the model unique in its ability to (i) allow endogenous decision-making by the banks under study in response to the evolving state of the system, (ii) simultaneously include (potentially) competitive effects (i.e., switching volume) and (potentially) market-expansive effects (i.e., PCA market growth), (iii) be compatible with system uncertainties and systematically address their influences, (iv) include many brands (>20), (v) only depend on status-quo data, and (vi) have a low computational demand (Agrawal and Schorling, 1996; Ankam and Bouguila, 2019; Cerqueti et al., 2015; Charan, 2020; Marasco et al., 2016; Morais et al., 2016). We do note that our model relied on many assumptions of exogenous variables, including PCA market growth, switching volumes, and digital capabilities. However, as the model mitigated the consequences of these parameter uncertainties by employing EMA, they do not compromised the model being fit-for-purpose. In fact, the model validation consistently concluded that the model structure was valid and that the model outcomes were plausible, although they might have some numerical inaccuracy. While the model it thus the first of its kind, it also relates to some existing market share models by (i) estimating the market share of a bank depending on the characteristics of this bank relative to the characteristics of other banks, which is also the case in conditional logit models (Morais et al., 2016), and (ii) taking the 'attractivity' of banks as a central concept in determining market shares, similar as the multiple existing statistical methods to market share modeling (Charan, 2020; Morais et al., 2016).

8.1.2 Discussion of the current state of the UK retail banking industry

While the PCA market had been historically stable in terms of relevant players, their competitive positions, and their (lack of) competitive differentiation, the rise of digital challenger banks resulted in an unprecedented shift of PCA market shares and a consequent digitalization transition (Accenture, 2018; FCA, 2022a,b; FCA and CMA, 2018; SMF, 2018; UK Finance, 2019). In this study, we identified multiple factors that the PCA market historically had not encountered but which had a critical facilitating role in this successful rise of digital challengers. These factors include (i) the political and regulatory environment (e.g., increased competition and sustainability requirements) (DBIS, 2015; FCA and PRA, 2014; HM Treasury and BEIS, 2019), (ii) technology and innovation (e.g., digital-only banks) (FCA, 2022a,c), (iii) customer behavior and demand (e.g., transparency, multi-banking, convenience) (FCA, 2021, 2022a), and (iv) macro-and socio-economic developments (e.g., low-interest rate, demography) (Accenture, 2021; FCA, 2021; Payments Authority, 2014-2021). The identified factors are in line with observations from different industries, which previously concluded that *"external forces and exogenous shocks (e.g., technological innovations and new regulations) can strongly influence the functioning of a market, and they often induce firms to change their competitive strategies"* (Modis, 2011). In addition, Giesen et al. (2010) showed that indeed in periods of extensive industry change, companies should harness disruptive innovations and pursue new customer segments or dislodge competitors to stay competitive.

In all, the nature of these factors also implies that a new retail banking landscape is evolving. That is, we expect that these factors will continue to shape the retail banking industry even after a completed digitalization transition. To gain some insight into what these influences might entail, we estimated the following future trends in the underlying direct drivers of PCA market share dynamics. First, we identified multiple factors that imply an imminent stagnation in the PCA market growth, including (i) an inherent behavioral difference between going from one PCA to two PCAs, and going from two PCAs to three or more PCAs (FCA, 2022a; FSCS, 2022) (Expert 2), and (ii) small population growth (Office of National Statistics, 2021). On the other hand, we identified multiple factors that imply a possible upswing in switching volumes, including (i) higher reported switching intentions among consumer surveys (Deposit solutions, 2021; FCA, 2021; Payments Authority, 2022), (ii) generational shifts (Trajectory, 2016), and (iii) an increased tendency towards switching as the upswing in PCA market growth stagnates (Expert 2). While the upswing in switching volumes thus hints that further market share changes could theoretically be imminent, its potential impact is subject to the many system uncertainties that identified above and which we investigated using the simulation model. Unfortunately, the accuracy of our predictions could not be further discussed, as there is no available literature that has made similar predictions on the UK retail banking industry.

8.1.3 Discussion of model outcomes

While evaluating the model on 12,000 plausible future scenarios, we observed that (i) in all scenarios, the decrease in the PCA market share of the big 4 banks was small and either stabilized or continued in (smaller) magnitude towards the end of the simulation time (decrease from 0.610 to value in range 0.605-0.590), (ii) this decline in market share was absorbed by an increase in the market share of midtiers, (iii) underlying the small net decrease were small subsidiaries that gained customers, whereas large subsidiaries lost customers, (iv) a shock event step-increased the PCA market share of big 4 banks but did not change the observed dynamics, and (iv) not all banks adopted a sustainable business model.

During scenario discovery, we furthermore observed that (vi) low PCA market growth and moderate to high consumer preference towards the banks' service quality significantly contributed to a stagnation in the decline of the big 4 market share (final market share > 0.602), (vii) besides the previously described variables, additional low consumer preference towards banks' sustainable operations and moderate to high consumer preference towards banks' digital services significantly contributed to highly desirable outcomes (final market share > 0.603), (viii) these same four described variables significantly contributed to highly desirable outcomes after a shock event (final market share > 0.624), and (iv) very undesirable outcomes (final market share < 0.595) could not be significantly attributed to specific variables.

The changes in PCA market shares can be traced back to the performance of banks on the bank features

Observation one implies that PCA market shares are quite robust (i.e., between 0.5-2% decrease) to different factors (i.e., system uncertainties) such as the customer switching volume, PCA market growth, consumer choice of bank behavior, and different types of sustainable banking implementation strategies (e.g., being a leader or follower). We validated this finding during the discussion with the Feedback Panel, in which it was concluded that while the rough numerical results could not be validated, the model behavior corresponds to what might be expected of the real-world including the small range in outcomes when exploring all model uncertainties (FCA, 2022a,c; SMF, 2018).

Observation two concerns the market share migration towards mid-tier banks, which is an observation that was not in line with this author's expectations and those of the Feedback Panel. This is because the historical market share of the mid-tiers has been stable even throughout the disruptive innovation introduced by digital challengers, and because mid-tiers are often regarded as the banks with little resources to expand (FCA, 2022a; Guidehouse, 2021). We identified two possible explanations to this discrepancy: (i) mid-tier banks are currently not capturing their full potential, meaning that they face some barriers that prevent them from obtaining the market share that they are predicted to gain based on our simulation of consumer choice of bank behavior, or (ii) the simulation model is inaccurate and some control variable is missing, resulting in disproportional market share gain by the mid-tiers. Towards the first explanation, we identify a role for increased digitalization. That is, the mid-tiers tend to outperform the other banks on sustainability but underperform on digital capabilities. As such, our model implies that if this gap in digital competence is closed, the mid-tiers might obtain a good competitive position that allows them to gain market share.

Observation three, in turn, implies that the smaller subsidiaries within the big 4 category are more attractive to consumers than the big subsidiaries because they perform better on the bank features. Indeed, during model validation, we found that the initial bank feature scores of the smaller subsidiaries are generally superior to those of the bigger subsidiaries. Interestingly, however, is that these smaller subsidiaries are often more specialized than the large subsidiaries, which often serve "a bit of everything" (Feedback Panel). As such, one would not directly expect that the smaller subsidiaries have superior performance on all the bank features. We explain this discrepancy as follows. The competitive differentiation of the smaller subsidiaries allows them to target a specific niche of customers with specific products, and as such, these customers are likely satisfied with the product and service that they receive. As happiness is indirectly linked, through mood, to perceived service quality, trust and service outcome, these consumers will likely give their banks better ratings in consumer surveys (Hellén and Sääksjärvi, 2011). Indeed, combining figures from 13 different UK market sectors, the UKCSI (2011) found that as a general rule, for every 10% of market share gained there was a 1.5% drop in customer satisfaction. As a result of the better overall performance of the smaller subsidiaries, other consumer may start to get attracted, thereby explaining the increase in market share. This latter line of reasoning is in line with recent performance reports, as for instance the smallest subsidiary of the Lloyds banking group reported the highest growth in the number of PCA customers in the past year (Lloyds Banking Group, 2021). These findings, however, also imply that there may be some sort of trade-off between being more specialized, getting higher overall ratings, and, thereby, gaining market share, and being less specialized, serving more customer segments, but at the risk of future market share loss.

Finally, observation four implies that a one-time shock event is not capable of causing a major offset in the dynamics of customer market shares. This finding is, fortunately, not in line with historical records of the financial crisis in 2008 in which the fail of Lehman Brothers caused a panic that sparked the worst global recession (Guardian, 2022). Rather, it is more in line with the findings of the Bank of England (2022), who concluded that even if a (major) UK bank were to collapse, customers would be able to access their accounts, and banks could broadly provide services as normal. As such, while observation four by no means is a complete representation of the (monetary) factors that aid towards a banking crisis, the finding does imply that a single shock-event will readily be adsorbed in the PCA market.

Variables significantly contributing to the stagnation in customer market share decrease of big 4 banks both confirm and contradict previous studies

Observation six, seven, and eight collectively imply that low PCA market growth, low consumer preference towards sustainability, and moderate to high consumer preference towards digital capabilities and service quality significantly contribute to limiting the market share decrease of big 4 banks to max. 0.7%. Here, we reflect on these four variables.

First, the contribution of low PCA market growth was discussed in detail during the validation. In short, as PCA market growth was found to be the main driver of the observed customer market share dynamics, limited growth results in limited dynamics. This observation is in line with previous findings on the digitalization transition, in which the sudden upswing in PCA market growth (while switching volumes remained stable) was found to be the direct driver of the unprecedented changes in the customer market shares (FCA, 2022a).

Second, low consumer preference to sustainability might be advantageous to big 4 banks, as they tend to underperform on this criterion relative to other banks. That is, low consumer preference to sustainability will result in decent attractivity of the big 4 banks relative to other banks, as the big 4 banks score decent on the other bank features. We do note that the underperformance of the big 4 banks on the sustainability feature is quite surprising, as the ESG scores that were used as proxies towards sustainability are often criticized for disproportionately affecting smaller banks *"that are not as well-equipped with sophisticated corporate social responsibility (CSR) or sustainability departments"* (Arabesque, 2021). Moreover, ESG scores generally raise concerns of 'greenwashing' and misrepresenting a company's sustainability credentials, but unfortunately these limitations could not be addressed at the time of this study. This is because the latter will require capacity-building and technology to build a better functioning sustainability data landscape. While the current proxies for the sustainability of a bank are thus the best available, they may have projected numerical inaccuracy into the model results.

Nevertheless, we find another interesting implication of low consumer preference if we combine this observation with observation five (i.e., not all banks adopting sustainable business models). Together, they imply that the commoditization of the strategic advantage of a sustainable business models does not cause the stagnation in big 4 banks' market share decrease. This is against the claims of previous studies, which argue that the potential to improve banks' (financial) performance through sustainable business models reduces over time due to commoditization (Lymbersky, 2008; Skinner, 2021; Wright, 2002). Instead, observation five implies that sustainable business models cannot be commodified organically based on PCA market pressure.

Third, high consumer preference to digital capabilities may contribute to the stagnation as they are the digital capabilities of banks are exogenously scaled to converge. Specifically, due to this scaling operation, the banks are characterized with very similar digital features scores by the end of the simulation. If the consumer preference towards this score is high, then at the end of the simulation there is little competitive differentiation among the banks. The latter will result in little changes in the customer market shares, and thereby contribute to a stagnation in the market share dynamics. Previous literature has also found similar explanations to the historically stable market shares in the PCA market, attributing this stability to "banks being all the same" (Revealing Reality, 2017).

Finally, the high consumer preference to service quality might be an artifact of the simulation model. This is because service quality is highly determinant of customer attrition (as its weight is constantly 0.7), and if the weight of service quality towards customer acquisition is also high, banks' attrition and acquisition scores become very similar. The latter would result in a small net effect on the customer market shares, and, thereby, the observed stabilization.

Switching volumes and banks' attitudes to adopting a sustainable business model do not significantly influence the customer market shares

Observation six, seven, and eight also collectively imply that within the current system composition, specific implementation strategies (e.g., leader, follower) do not significantly influence the dynamics in customer market share. That is to say, banks' attitudes to adopting a sustainable business model do not influence their competitive position. The observations furthermore imply that switching volumes do not have the capacity to significantly influence market shares. During model validation, we found that this is due to banks being unable to capture a significant share of the switches, leading to the magnitude of the switching volume being cancelled out during the process of customer attrition and acquisition. This latter finding might explain why, against the UK government's expectations, switching volumes do not facilitate competition within the retail banking industry (CMA, 2014).

8.2 Theoretical implications

This research aimed to investigate the effect in the customer market share of UK retail banks when they adopt sustainable business models given their competitive environment. To this end, we used a simulation model that assessed a variety of future scenarios, thereby giving a broad overview of what might happen in the future. Here, we discuss the theoretical implications of these findings and this study in general, thereby furthering the understanding of how the strategic decision-making of bank managers influences their competitive position.

8.2.1 The definition of sustainable banking

By using sustainability as a driver for customer market shares, we implicitly positioned ourselves in the academic debate on whether profit is contained within the notion of sustainable banking, and within sustainability in general. As we regarded sustainable banks as those with high ESG scores, we sided with scholars that exclude profit from the definition of sustainability (Montiel and Delgado-Ceballos, 2014; Rey et al., 2019; Schaffmeister et al., 2021). We based this decision on the synthesis of literature that allowed us to demonstrate that sustainability could be a driver of profit (notably defining profit by the number of customers) within the retail banking industry. Moreover, excluding profit from the definition of sustainable banking is in line with our claim that sustainable business models are a more unique kind of innovator's dilemma. That is, banks with a sustainable business model provide value-added (i.e., sustainable) services to their customers, and these values inherently cannot be monetary.

We furthermore add to the debate by modeling sustainability in an almost binary manner, with a sustainability feature score >0.85 being regarded as a sustainable bank. While we plotted the implementation strategies on a continuous axis between profit and sustainability, the decision to become sustainable thus had a binary effect. As such, the intention to become sustainable (i.e., the implementation strategies) did not define the sustainability of a bank. We thereby argue that there is some threshold for being regarded as sustainable, and approaching sustainability as a continuum is not valid. That is, while some banks might have more positive impacts on society and the environment than competitors, it is only when these impacts compensate for all their negative impacts that they can be classified as sustainable. The term "compensate", in turn, is also a subjective matter which requires further specification in the future. Here, we argue that compensation entails that the net effect of banks' externalities should be sustainable (Van den Bergh, 2010).

8.2.2 Modeling market share dynamics in light of a potentially disruptive strategic innovation

To the best of our knowledge, there are no previous modeling studies on the disruptive potential of strategic innovations. We identified two barriers to this deficit: (i) previous works on strategic disruptive innovations show that the impacts are hard to predict in general due to many uncertainties (Birnbaum, 2005; Si and Chen, 2020), and (ii) existing market share models depend on historical data which is fundamentally incompatible with modeling the impact of a potential strategic innovation on which data is not available (Charan, 2020; Heckbert et al., 2010; Marasco et al., 2016). In this study, we show that a simulation model based on the language of game theory and using the concepts of ABM while being subject to EMA is a suitable modeling method that tackles these challenges.

As proof-of-principle, we applied this model to the UK retail banking industry. The observed range in the dynamics of the customer market shares under different future scenarios, both numerically and behaviorally, collaborate previous claims that the exact impact of strategical innovators dilemmas are hard to predict (Birnbaum, 2005; Si and Chen, 2020). The diversity in the plausible future states and the associated decisions of bank managers, in addition, adds evidence to the previous claims that competition cannot be reduced to a static concept (Marasco et al., 2016). We furthermore collaborate previous claims that the effects of strategical decisions on different topics (e.g., price and sustainability; whether modeled endogenous or exogenous) cannot be studies in isolation, as our simulation model displayed interdependencies in their effectiveness (Charan, 2020).

8.2.3 The disruptive potential of sustainable business models

Previous studies showed that banks' sustainability activities are associated with the bank's market-, leadership-, and owner characteristics as well its risk, (financial) performance, and value (Esteban-Sanchez et al., 2017; Gillan et al., 2021; Laguir et al., 2018; Simpson and Kohers, 2002). In this study, we show that sustainable business models are not significantly associated with banks' PCA market share. This finding has two alternative implications. First, while our literature synthesis revealed that sustainability may both directly and indirectly increase the number of bank customers, sustainable business model may lack the capacity to actually do so. In this case, our findings contradict previous works that argue in favor of sustainable business models regarding the banks' performance (Accenture, 2020; McKinsey, 2019; Raut et al., 2017; Yip and Bocken, 2018). These previous works notably have not used modeling methods and have failed to consider the competitive environment of banks, including the continued digitalization transition. On the other hand, our hypothesis that the effect of sustainable business models on a bank can be reflected by its number of customers might be invalid. The latter case is supported by the finding from Wang et al. (2022) who showed that sustainability is merely a facilitator for the adoption of innovations within a company, and thus may only indirectly contribute to the number of customers. As such, sustainability might be associated with the factors described at the start of this paragraph, but might not the driver of these correlations. In this latter case, our inability to identify an effect of sustainable business models on customer market shares might thus be caused by the effect of sustainability not being modeled correctly.

Nevertheless, we can argue that the direct effect of sustainable business models on PCA market shares is of minimal disruptive potential. We attribute this limited effect to banks' inability to competitively differentiate themselves on the basis of sustainability. In the end, rather than absolute, it is thus the relative attractivity of a bank compared to others that has the greatest significance on their market share (Charan, 2020). Additional evidence to the minimal disruptive potential comes from the observation that market pressure alone was not sufficient for all banks to adopt a sustainable business model, with the latter being usually the case with disruptive strategic innovations (Birnbaum, 2005). As such, we can confirm one of the barriers that bank managers face while considering the adoption of a sustainable business model; a wide-scale disruption of the PCA market is not imminent (Accenture, 2020).

8.3 Practical implications

The exploratory analysis conducted in this thesis represents a first step in understanding the quantified impact of sustainable business models on customer market shares, and, conversely, how market share dynamics impact policy in the long run. Hence, the policy recommendations provided in this section do not feature specific, quantified metrics, but rather point relevant actors towards a general policy direction given the conclusions drawn.

8.3.1 Recommendations to governmental institutions

One of the objectives of this study was to explore the range of future dynamics in the customer market shares and their implications for the UK retail banking industry, as these insights are useful sources of information for the design of new regulator policies. Notably, the policy of the past decade was designed to increase competition in the UK retail banking industry though the introduction of CASS as well as by facilitating bank licensing applications and lowered capital and liquidity requirements (DBIS, 2013, 2015; FCA and PRA, 2014; Prorokowski, 2011). CASS was introduced in 2013 and the first new entrants (i.e., the digital challengers) came in 2018. Interestingly, standalone CASS did not have the desired effect as *"the PCA providers with the highest satisfaction levels have not been able to gain significant market share, which is not what one would expect in a well-functioning competitive market"* (CMA, 2014). On the other hand, the digital challengers did result in competition, as reflected by the 8% customer market share that they captured between 2018-2021. Here, based on the model insights, we advise regulators on the effectiveness of these two existing policy levers. In addition, regulators have indicated that they want to increase sustainable practices in the UK retail banking industry, as currently only c.20% of the relevant PCA providers has a sustainable business model (HM Treasury, 2021; HM Treasury and BEIS, 2019). As such, we also advise on the policy levers that could contribute to this goal. The recommendations are as follows:

- **Focus on increasing competition through unique new entrants**. Increased switching volumes have little effect on dynamics in customer market shares, as the competitive differentiation between banks is too small for them to capture a significant share of the switching volume. While the CASS thus might lower the sunk costs of switching bank accounts, increased switching volumes as facilitated by CASS will have limited effect on increasing competition. Instead, focus on the policy that facilitates unique new entrants in the market. This is because these unique new entrants (as the digital challenger banks once were) have the capacity to introduce significant shifts in competitive positions if consumers value their unique trait. In addition, as demonstrated by the digitalization transition, these new entrants with strategic innovations have the potential to benefit a broader set of consumers without having to switch providers. This is because their unique trait could potentially be commoditized.

- **Introduce additional incentives for retail banks to adopt sustainable business models.** The model has demonstrated that organic market pressure from the PCA market is insufficient to introduce a sustainability transition in the UK retail banking industry within the next seven years. As such, to ensure the transition, additional incentives in the form of e.g., regulations are needed. We note that these incentives should be directed at banks, as incentives for customers (such as a monetary bonus) for choosing a sustainable bank are not effective. The latter is demonstrated by the observation that even in the case of high consumer preference to sustainability, the customer market share dynamics of big 4 banks were at max. 2%. On the other hand, the true need for the additional incentives can only be determined if the whole retail banking sector is considered and not just the PCA market. That is, it is currently unknown if sustainable business models in e.g., the saving accounts market do yield a competitive advantage, and as such, if market pressure from this sector is sufficient to generate a sustainability transition. Regulators should thus determine this true need, but should prepare to introduce these additional incentives sooner rather than later.
- **Facilitate consistent data collection on a number of bank KPIs and make it publicly available.** This research has been limited by the lack of databases that report on all the banks (not just the Big Eight high street banks) that operate in the UK retail banking industry. To aid future research onto the market shares and thereby the competitive positions of banks by both regulators and the private sector, data should be collected consistently from every bank to ensure its compatibility.

8.3.2 Recommendations to bank managers

The second objective of this study was to advise bank managers on their strategic decisions regarding the adoption of a sustainable business plan, given all other possible corporate strategy combinations that could be employed by their competition. Here, modeling advantageously allowed for the generation of robust corporate policy advice that answers questions such as "is being an innovator worth the risk?". However, we observed that sustainable business models are not associated with retail banks' PCA market shares, and as such, we advise on the alternatives that bank managers might consider to influence their competitive position. The recommendations are as follows:

- **Do not focus on building customer market share.** Changes in the customer market shares are mostly driven by PCA market growth. Within the current market, this growth is mostly caused by customers opening secondary (or even tertiary) accounts. As these accounts are often operated with a very low margin (if not at a loss), banks should only try to capture these customers if they feel confident that these secondary banking relationships can be transformed into primary accounts. In addition, under current conditions in the system, banks do not seem to be able to capture enough share of the switching volumes to make a significant impact on their market share. As such, focus on the retention of current customers and offering services that maximize their wealth. The economic logic behind the latter is simple; more customer wealth is more wealth that banks can help their customers manage.
- **Redefine how the customer value proposition is designed.** While sustainable business models might not increase customer market share, they do attract customers that are more loyal and less price-sensitive (Azmi et al., 2021; Mackey et al., 2007; Rizan et al., 2014; van Esterik-Plasmeijer and Van Raaij, 2017). As such, the adoption of a sustainable business model might have non-tangible side effects that are favorable towards the bank. It is, however, important to ensure that the customer value proposition is aligned with the business model to prevent greenwashing. To this end, banks may employ a multidisciplinary team of research, marketing, strategy, and retail product specialists who, together, compile and present holistic solutions.
- **Set up specialized PCA products.** The bulk of PCA providers is competing for the same customers, with very limited competitive differentiation. Try to focus on an underserved small customer segment by reaching beyond traditional bank offerings using better banking propositions that expand the customer choice. To this end, banks can partner with third-party providers (such as insurers and merchants) that serve customers' needs from different angles (Accenture, 2020). One could, for instance, try to offer more personalized services such as automatic budgeting tools. These kinds of products are in line with consumers' increasing preference towards convenience.

- **Use monetary incentives to compensate for a lacking performance on sustainability, digital capabilities, or service quality.** Monetary incentives effectively dampen the dynamics in customer market shares, which can work in favor of a bank by limiting its market share decrease, or not in favor of a bank by limiting its market share increase (FCA, 2022a; MoneySavingExpert, 2022). As such, banks should use behavioral analytics to better understand their (future) customers to create interventions and offerings, such as automatic investment solutions, that can positively change their customer relationships.

- To mid-tier managers: **Investigate the potential to capture market share.** According to this study on the consumer choice of banks behavior, mid-tier bank will gain market share as big 4 banks and scale challengers are losing it. While it is currently unsure whether this model outcome is valid, mid-tier banks might want to investigate their biggest barriers to customer acquisition and evaluate if costs of addressing these pays off a potential increase in customer market share.

We must note, however, that the generated insights and consequent recommendations on the different implementation strategies have not considered how these strategies work in practice. Charitou and Markides (2003) suggest that the correct strategy for a specific company depends on motivation to respond and ability to respond (Chen and Miller, 1994). The former is determined by factors such as the rate at which the innovation is growing and how threatening it is to the main business, whereas the latter is determined by factors including the company's portfolio of skills, its resources, and the time it has at its disposal. The heterogeneity among the banks in the UK retail banking system will thus limit which banks can adopt which implementation strategy (Sandström et al., 2009). This was not considered in the model, which makes the presented insights possibly inaccurate. In addition, the presented recommendations might not be the best course of action for specific banks given their resources, and banks thus ought to evaluate their own position towards the feasibility of the recommendations.

What is more, if banks do decide to adopt a sustainable business model for ecological reasons, banks ought to define a demarcated strategy. Lagasio et al. (2021), for instance, have previously demonstrated that banking consumer's preferences and responses towards different CSR initiatives (ethical behavior towards the environment, social inclusion initiatives, and financing eco-sustainable projects) differ with diverse demographic characteristics (age, geographic origin, and type of employment). These differences in consumer preference have not been studied in the model, and, as such, banks should investigate which sustainability initiative matches their company profile and target customers best.

8.4 Model limitations and future work

Given the short research period of this master thesis, there is an abundance of associated limitations that should be considered and contextualized. To begin with, the customer market share simulation model is an abstraction of reality, featuring the PCA market with twenty actors. In addition, the consumer choice of bank behavior is applied at an aggregate level, and fundamentally assumes that an increase in relative attractiveness results in higher market share. As there are plenty of other factors to consider, we include a list of the most relevant limitation of our analysis below. For simplicity and brevity, we also immediately suggest future research opportunities to address the limitations.

8.4.1 Limitations of the simulation model and suggested improvements

In this study, we presented the first ever attempt to model the customer market share dynamics that emerge from the strategic interactions of banks. As such, there are multiple model characteristics that currently limit the numerical validity of the model outcomes. Generated absolute quantitative results should therefore not be taken as trustworthy, but rather be interpreted as qualitative representations of system behavior conform to the exploratory objective of this model. Below, we discuss the limiting model characteristics and classify their suggested solutions into either being an improvement to the existing model structure or as an extension of the model structure. The former entails that the improvement can readily be implemented within the existing model code, whereas the latter requires the design of additional model structures and thus more extensive model code.

Improvements to existing model structures

- **Determining the feature weights more accurately**: We determined the bank feature weights based on the synthesis of consumer surveys. As such, the interdependencies between these feature weights have been disregarded and the weights might be inaccurate. While the EMA approach overcomes the limitations to a certain extent by exploring the parameter uncertainties, future research should focus on gaining more detailed insight into the non-linear relations between the feature weights. To this end, we suggest two methods:

Subjective deduction: In this case, the weights are determined by subjecting consumers to pairwise comparison of the bank features. That is, consumers will be asked to rank the different bank features in pairs to determine which of each bank feature is preferred overall (Meißner and Decker, 2009). In addition, consumers could be asked which pairwise rankings are hard to make and which ones are easy, besides allowing consumers to give indications of which pairs of bank features have a synergistic effect on their choice of bank.

Empirical deduction: In this case, the weights are determined by studying the predictive value of bank features on consumer choice of bank behavior. That is, the predictive value of the bank features towards customer attrition and acquisition could be determined though using a prediction model, such as a small neural network (e.g., a multi-layer perceptron) (Winter et al., 2021). While these machine learning models can advantageously be designed to capture non-linear relationships, they also would require historical consumer choice of bank data (Jordan and Mitchell, 2015). The latter is not possible if this model is applied to predict future dynamics, but if, for instance, the digitalization transition would be replicated, this approach could be valuable.

- **Determining additional control variables for the attrition/acquisition score**: The used control variables were found to influence the numerical outcome of the model, but especially the control variable for the acquisition score does not capture the full complexity of the consumer choice of bank behavior (Feedback Panel). As such, future research should focus on inventorying all (control) factors that are relevant towards the consumer choice of bank, and consequently focus on how these factors can be modeled in a way that they meet the set requirements of the control variables. That is, the control variables (i) must be adaptive to the current state of the system (i.e., depend on time t), and (ii) should represent a concept that is relevant during the entire simulation time.

Extensions of the model structure

- **Modeling PCA market growth and switching volumes endogenously**: We modeled the PCA market growth and switching volumes exogenously, thereby limiting the range of behavior that could possibly be generated. This, in turn, could have hampered the discovery of interesting and unexpected system evolutions under the evaluated scenarios. Future research could therefore consider modeling the mentioned variables endogenously with the use of sub-models. We do note that this would require more knowledge on the consumer behavior that results in their decision to switch or open an additional PCA. To this end, researchers might want to use the Analytic Hierarchy Process (AHP) method, which organizes and analyzes complex decisions using math and psychology (Vaidya and Kumar, 2006). That is, alternative decisions (such as to switch or not) are addressed by breaking the choice problem into a hierarchy of smaller problems until decision criteria have been reached. Consequently, the magnitude of each criterion is determined using pairwise comparison.

- **Including consumer characteristics**: While the model does provide insights into the changes in customer market shares, Expert 2 suggested that studying the asset market shares is necessary follow-up research. This is due to traditional banks valuing their KPI of customer deposits more than their KPI of number of customers, and as such will likely only be motivated to act if the former is dynamic. During the digitalization transition, for instance, the 8% shift in consider market shares resulted in only a 1.2% shift of the total consumer deposits (FCA, 2022c). Future research should therefore include consumer characteristics, such as their wealth, to study asset market share dynamics via the repurposing of our simulation model. Including consumer characteristics could also serve the purpose of increased numerical accuracy in the model, as the Feedback Panel expressed the importance of considering different age groups and banking personalities in choice of bank behavior. That is, for instance, there might be some upper limit to the amount of people that considers choosing a mid-tier bank, possibly explaining the discrepancy between our model results and expectations on the dynamics of mid-tiers market share.

8.4.2 Future research topics

Based on the findings of this study, we argue that there are multiple interesting future works that can follow this study.

- **Different applications of the model**: Our agent-based customer market share dynamics model can easily be generalized to different markets (e.g., saving accounts, credit cards), sectors (e.g., insurance, telecom), utilities (e.g., number of contracts), and different geographical scopes under the condition that consumer behavior is consistent within this scope (e.g., the German retail banking sector). This generalization would require the researcher to (i) establish relevant characteristics of the brands (i.e., the model entities) that influence the consumer choice of bank behavior, (ii) identify suitable proxies towards the selected brand features, (iii) identify relevant control variables for the consumer choice of brand behavior to increase numerical accuracy, and (iv) design relevant strategies for the entities that dictate their decision-making during the simulation. The first three steps are dependent on the system that is going to be researchers, whereas for the latter the same strategies as in this study may be taken (e.g., Copy, Adapter, etc.).

- **The role of mid-tiers**: Based on the current consumer choice of bank behavior, our model predicted that mid-tiers would gain the most customer market share, which is not in line with what experts expect. As such, it is the question if this is due to inaccurate model outcomes (as addressed above by the need for more control variables), or because mid-tiers are somehow constrained in their potential to gain customer market share. As this study has focused on the big 4 banks, future research could focus on the remaining bank categories to validate their model outcomes. This would, for instance, include more expert validation using managers from mid-tier banks.

- **Calculating elasticities of bank features**: In regression models for market share prediction, the impact of an explanatory variable X (in this case a bank feature) on the dependent variable Y (i.e., market share) is quantified through the use of so-called elasticities. Mathematically, it can be seen as the logarithmic derivative of Y with respect to the logarithm of X (Morais et al., 2016). Our current model design effectively handles the interdependencies between the bank features, but is not able to identify individual influences of the bank features (because they cannot be modeled in isolation). Future research might thus be able to get inspiration from statistical methods on how to isolate this effect. If this is successful, the effectiveness of the bank features in terms of their contribution to the number of customers can be benchmarked against costs to compute Return on Investment (ROI). This latter statistic, in turn, can be used to better advise bank managers on their strategy.

- **Facilitating multi-objective decision-making for banks**: The model currently lets bank managers decide on the adoption of a sustainable business model based on the number of customers. In reality, however, bank managers are subjected to multiple-objective decision-making as they for instance balance investment costs with the payoff in customers and/or their deposits (as e.g., reflected by measures such as the ROI) (Charan, 2020; Reinartz et al., 2005). Future work could therefore study the decision-making of bank managers, including the relevant decision criteria to change their business model or not. These criteria can subsequently be introduced into the model to more accurately model the behavior of banks.

- **Including an "outside option"**: The model currently accounts for customers that switch their PCA account or open an additional one. There is, however, a different type of "switching" going on that might be more dynamic than the PCA market. This switching includes transferring money from a PCA to a saving account, shares, or digital currencies like bitcoin. This can be modeled if consumer deposits are monitored, and if such as "outside option" is available for consumers to choose. Including such an outside option has been previously reported by Marasco et al. (2016), who used a nonautonomous LV model in which an "outside option" was introduced that accounted for customers that chose a product/producer that was not among the ones considered in the model.

Regarding the usefulness of this study for Company X, which is an international consultancy firm providing business services on strategy, consulting, technology, and operations, the above future research suggestions provide tangible leads. Part of the suggestions namely addresses consulting-type questions, such as applying the simulation model to different sectors to advise the associated brand managers on their strategy or studying industry trends such as the "outside option".

8.5 Conclusions

In this study, we addressed the lack of understanding in customer market share dynamics that emerge through the collective effect of banks' strategic decisions regarding the adoption of sustainable business models. To this end, we developed and applied a novel simulation method for market share dynamics with both predictive and descriptive properties. Specifically, the design of the model uses the language of game theory in the context of agent-based modeling while being subject to exploratory modeling and analysis to understand the complexity of customer market share dynamics. This design advantageously allowed to include the relevant behaviors of customers and banks, being the consumer choice of bank behavior and strategical decisions on different topics (e.g., price and sustainability), respectively.

Prior to the modeling activity, we explored the current state of the UK retail banking industry. In doing so, we identified four factors that are shaping a new UK retail banking landscape and potentially underlie a future upswing in switching volumes. As such, we are the first to provide tangible evidence in favor of the legitimacy of previous claims that market share changes consequent to sustainable business models could be imminent.

With the simulation model, however, we showed that these market share changes are very marginal in the coming seven years. That is, the PCA market share of big 4 banks is robust (c.0.5-2% decrease) to different factors such as the customer switching volume, PCA market growth, consumer choice of bank behavior, and different types of sustainable banking implementation strategies (e.g., being a leader or follower). As such, we found that sustainable business models are not directly associated with PCA market share dynamics. We thereby conclude that the disruptive potential of sustainable business models is limited, i.e., that wide-scale disruption of the PCA market is not imminent. As to the mechanisms that do underlie the marginal changes in the market shares of UK retail banks, we identified a role for mid-tier banks that improve their digital capabilities, and, thereby, improve their competitive position. In addition, smaller specialized banks may capture some market share as they tend to outperform bigger banks on sustainability, digital capabilities, and service, but this growth in market share is limited as serving more customer segments is associated with less satisfaction and a consequent potential decrease in market share. As such, we conclude that the organic growth of smaller banks in the UK retail banking industry is limited.

The policy implications of these conclusions pertain mostly to retaining current customers by big 4 banks and fostering more competition in the UK retail banking industry by regulators. We believe, however, that bank managers should consider the ecological consequences of sustainable business models when designing their policies. Precisely because there is no direct link between sustainable business models and customer market share, one can adopt such a business model without fearing the competitive position. The plausibility of irreversible climate change does mean that investment in measures for dealing with these circumstances, and not just greenwashing, should be taken sooner rather than later. After all, the world goes where the money flows.

Appendix A

Expert interviews

To overcome gaps in data and gain insight into the developments into the UK retail banking industry, multiple semi-structured interviews have been performed. In these interviews, the interviewer prompted the interviewee to give an opinion / guesstimate on a specific predetermined topic, after which follow-up questions and discussion arose that were not planned in advance (Galletta, 2013). Note that the different experts were interviewed on different topics to cover as much content as possible in the limited time available to writing this thesis. The topics discussed were selected to fit the background of the experts. Below, we report on the outcomes of the interviews by summarizing the expert answers per topic.

A.1 Expert 1

Date: 29/04/2022
Expert profile: Researcher at global corporate consulting firm with over 5 years of experience on the topic of Financial Services, including banking and insurance.

A.1.1 The number of PCAs per bank

When asked about data concerning the PCA market shares in the UK, the expert said that this is not readily available. Many retail banks do not disclose this information, rather, they disclose the total amount of money (i.e. volume/assets) that is deposited in the PCAs. The FCA might hold data on this, but is not disclosing it either.

A.1.2 ESG feature

Arabesque is a well-trusted and internationally recognized provider of ESG data, and therefore probably the best source to start from. It must be noted that arabesque reports data for all subsidiaries of the same group. So, for instance, there is data reported for the Lloyds Banking Group, which includes input from the Lloyds Bank, Bank of Scotland, and Halifax, amongst others. There is thus no data available at these retail banks' individual level.

In addition, the banks that do not have reported data might be estimated, as Arabesque only has data on publicly traded companies. For Nationwide, it was advised to take the average ESG data of the big 4 banks, given that nationwide is also quite a large player. For the new entrants Monzo, Starling, and Triodos, it was advised to assume that they have a relatively high ESG score. Specifically, for the environmental score, the score should be >70 given that the new entrants are digital challengers without a large environmental footprint from a branch network. For the governance score, it is also advised to take a relatively high score, given that the new entrants aim to do banking "the better way". The society score may be the only one that is lower than average, given that charity work etc will likely not be their priority as a growing company that is trying to become profitable.

A.1.3 Rates and rewards feature

While rates and rewards are an often cited factor for switching bank accounts, expert 1 confirms that PCA accounts do not generate interest income, not do they generally cost money to consumers. He therefore suspects that the monetary incentives refer to the opening bonuses that many retail banks offer.

A.2 Expert 2

Date: 29/04/2022
Expert profile: A Managing Director who leads a global consulting firms' UK's Financial Services Strategy practice. The expert has over 15 years of experience in advising global clients across Retail Banking, Commercial / Corporate Banking, Wealth Management, and Capital Markets. Their primary work has involved developing business and operating model strategies for clients in response to changing internal strategies, industry trends, acquisition and regulatory requirements. The expert is also an active commentator on the Digital-only / neo banking landscape in the UK.

A.2.1 The definition of PCA

The expert has some critical notes on the definition of a PCA and how PCAs are used as a measure for how well banks' are performing. That is, PCA refers to a primary current account, so talking about two PCAs per Capita is not really valid as the second account cannot be a primary account. It is the primary account use that drives profit for banks through more transactions etc., and thus specific details on the money deposited per accounts is relevant. Nevertheless, the expert also acknowledges that documentation/data on this distinction is not existing, especially on a level that would be needed for research such as this thesis.

Only a naive observer would thus conclude that the number of PCA customers is equal to the number of good customers. As there are currently 1.85 PCAs per capita, there is one "good" customer (=primary account use) for every 0.85 "bad" customer (=secondary account use). Data on the wealth/PCA is, however, not existing so the extend of the discrepancy is not clear.

A.2.2 The reality of threat by new entrants

Yet, it is important to take the distinction between primary and secondary accounts into the bigger context. As the incumbents are losing PCA market share, it is the question if they are really worried about this transition. This has to do with asset market shares hardly changing, implying that while new entrants are gaining PCA market share, these accounts are mostly used as secondary accounts with low balances deposited on them. The expert indicates that incumbent banks are thus likely not yet really concerned with the PCA market share changes, and that they will only start to worry once their asset market shares are starting to be affected.

When prompted about the timeline of this change, and the feasibility of new entrants gaining asset market share, the expert indicated three necessary changes that need to happen. First, there is already evidence that a certain type of demographic consumers (young, tech-savy) are opening accounts at new entrants. As these consumers age, their wealth will also increase, meaning that the asset balance sheet will increase. Second, there will need to be a change in consumer behavior that can only be achieved through better banking propositions. That is, bank accounts are currently quite similar, and more personalized services could prompt the consumer to actually change their primary account to a new entrant. Third, the new entrants simply need to grow bigger to get a bigger balance sheet. Once the balance sheet is up, they can start to offer competitive pricing concerning interest rates on e.g. saving accounts, which they currently cannot due to limited funds available. The expert indicates that all three changes are not happening overnight, but that the next 3-5 years are critical. The new entrants will either blossom into full scale competitors, or they "die" in the interim as they are not profitable enough or as they are consolidated by bigger players.

In fact, the expert notes that the business model of new entrants is also what makes them vulnerable: they offer super-fast, well integrated digital services that make it really "easy" to keep using their current account as a secondary account. For instance, when you go overdrawn at a current account with a new entrant, that account automatically takes money from your primary account (which is often at an incumbent). There is generally thus no incentive to have a lot of deposits at the current account held with a new provider,

A.2.3 PCA market growth

The expert was presented with the PCA market growth projection and found it to be credible, with no further drivers of change to be added to the argumentation.

A.2.4 Future switching volumes

On CASS, the expert mentions that its presented switching volumes do not represent reality. Besides no 100% awareness, this is also due to people not using CASS for switching. He expects that in reality, <10% of the consumers are switching their bank account on a yearly basis. What is more, among this 10%, there seem to be quite some serial switchers, making the actual amount of consumers that switch even lower. When asked about the future performance of CASS, the expert thinks that CASS will not work better in the future, given that is has not started to effective increase switching volumes over the past seven years. That is, while CASS may have made switching more efficient, it has not changed consumer behavior and the expert also does not see this happening in the near future.

The expert therefore just expect there to be a minor upswing in the switching volumes due to different generations becoming of age (e.g. Gen Z switch more often). If asked for a prediction for the upper limit of the uncertainty interval of future switching volumes, the expert "would be surprised" if they hit 15% at the end of the simulation time.

On the other side, there may be two types of events that cause the switching volumes to temporary increase. The first would be a trigger event, in which a sizeable bank falls and all its customers need another PCA provider. The second is a shock event, in which a new entrants like JP Morgen Chase becomes credible fast.

A.3 Feedback Panel

Date: 15/06/2022
Expert profile 1: A Managing Director who leads a global consulting firms' strategy and consulting capabilities in banking, insurance and capital markets in the Netherlands, ensuring his team is helping clients to define and implement winning strategies, enabled by innovation and digital technology. the expert has over 15 years of experience with different areas of the banking industry, including retail banking, business banking, and wholesale banking, in lending / mortgages / leasing, savings and in payments / transaction banking. In recent years, they have supported banks in finding and executing a strategic response to the impact of innovation and disruptive change on their businesses. Focus areas are among others open banking and platforms, digital attackers, data-driven enterprises.

Expert profile 2: A Manager who leads a global consulting firms' Dutch research department on the topic of Financial Services. The expert has 6 years of experience with retail banking.

Expert profile 3: A Manager in a global consulting firms' Dutch Strategy practice advising primary financial institutions on multiple business topics: Long Term Strategy / Strategic Plan Definition, New commercial model, customer segmentation & service model redesign, Digital and Omnichannel Transformation, Marketing strategy (Go to Market, Brand & Product design, pricing), and Post Merger integration. The expert has 8 years of experience with the banking industry.

Expert profile 4: A Manager in a global consulting firms' Dutch Strategy and Consulting practice advising on the latest digital innovations, including FinTechs, compliance, and digital business models. The expert has 8 years of experience with retail banking.

Expert profile 5: A Analyst in a global consulting firms' Dutch general Strategy and Consulting practice what works on a variety of topics in different sectors. The expert has 6 months of experience with retail banking.

Appendix B

Supporting explanations, figures, and tables

B.1 Estimations of the number of customers per bank

The most recent, publicly available, and detailed overview of current account market shares is from RFi Group (2018) that reported the following shares: Lloyds Banking group (24%), Barclays (15%), NatWest (14%), HSBC (12%), Santander (12%), Nationwide (10%), TSB (5%), and Virgin Money (2%). The reported Lloyds Banking Group, HSBC, and NatWest shares include their subsidiaries. The big 4 thereby held 65%, the scale challengers 29%, and the mid-tiers plus the digital challengers, by implication, held 6%. These findings are reasonably in line with findings from the FCA (2022a), which reported that in 2018, the big 4 held 68%, the scale challengers 26%, the mid-tiers 4%, and the digital challengers 1% (see Figure 3.1). The observed differences can likely be explained by the research sample that was used by the FCA. Specifically, they included only three of the four scale challengers (Santander, Nationwide, Virgin Money UK, and TSB), but did not specify which bank was excluded. In addition, they only included two mid-tier firms in their analysis, again without specifying which ones. As such, we used the market shares as reported by RFi Group (2018) as a starting point. Given the trends in the market that the big 4 and the scale challengers are losing shares, and in line with the FCA (2022a) observations, we estimated that the big 4 currently hold 61% of the market shares, the scale challengers hold 27%, the mid-tier banks hold 5%, and the digital challengers hold 7%.

In turn, the market shares within the big 4 category were determined based on the reported distributions of RFi Group (2018). For example, Barclays held 15%/65% = 23% of the market shares in 2018 within the big 4 category, and is therefore now assigned 23% of the 61% of market shares that the big 4 category holds in 2021. As most of the big 4 banks are comprised of subsidiaries, we used the advice of Expert 1 to distribute the market shares among the subsidiaries based on the "consumer deposit" volumes that are reported in the annual reports of banks (Bank of Scotland, 2021; HSBC Group, 2021; Lloyds Banking Group, 2021; NatWest Group, 2021; Royal Bank of Scotland, 2021).

Among the scale challengers, we distributed the market shares based on yearly reports. Nationwide, for instance, is the only to have specific statistics on the market share of the current account market, namely 10% (Nationwide, 2021). TBS has had some controversy over the past year and we observed that it has been losing customers from 2018 onward (see Figure 3.4). We therefore attributed a one-percentage point lower market share compared to 2018. Similar observations were made for Santander, resulting in the same reduction in its market shares. The market share of Virgin Money was held the same relative to 2018.

Next, the market shares of the mid-tiers were also based on the "consumer deposit" volumes that they reported in 2021, although the AIB Group had reported these numbers last in 2019 (AIB Group (UK) p.l.c., 2019; Bank of Ireland, 2021; Danske Bank, 2021; Metro Bank, 2021; the Co-operative Bank, 2021).

Finally, the market share of the digital challengers was distributed based on the reported number of customers, with the assumption that both starling and Monzo have a similar customers and similar services.

TABLE B.1: List of UK retail banks and relevant statistics

Bank category	**Market share of category**	**Bank (groups)**	**Market share**	**Subsidiaries**	**Market share**
Big 4	61%	Lloyds Banking Group	23%	Lloyds Bank	13%
				Bank of Scotland	7%
				Halifax	3%
		Barclays	14%		
		NatWest Group	13%	NatWest	8%
				RBS	4%
				Ulster Bank	1%
		HSBC Group	11%	HSBC	10%
				First Direct	1%
Scale challengers	27%	Santander	11%		
		Nationwide	10%		
		TSB	4%		
		Virgin Money	2%		
Mid-tiers	5%	AIB Group	0.6%		
		Bank of Ireland	1.1%		
		Co-operative	1.4%		
		Danske	0.8%		
		Metro Bank	1.1%		
Digital Challengers	7%	Monzo Bank Limited	5%		
		Starling Bank Ltd	2%		

B.2 Supplemental figures for model conceptualization

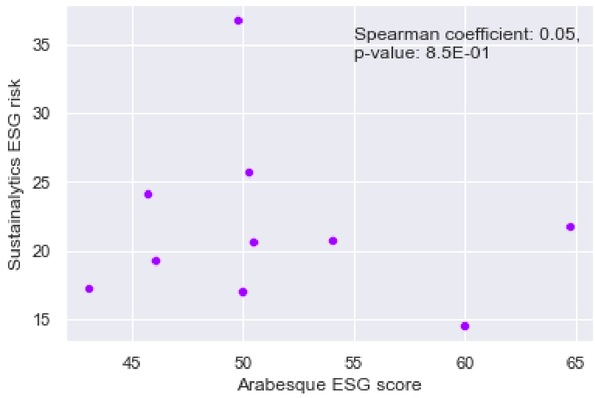


FIGURE B.1: Correlation between the proxies for sustainability.

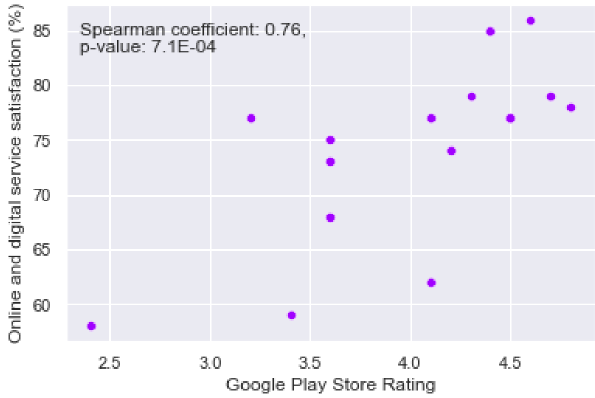


FIGURE B.2: Correlation between the proxies for digital capabilities.

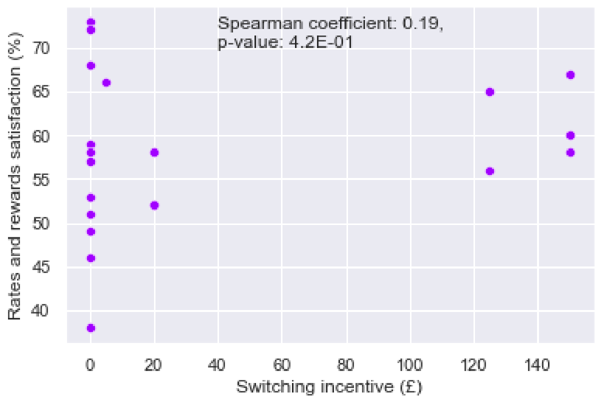


FIGURE B.3: Correlation between the proxies for price.

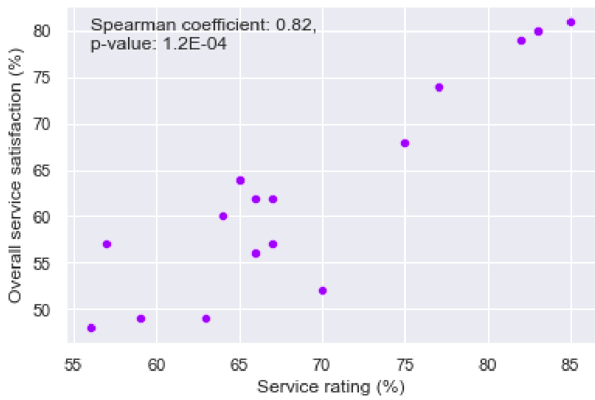


FIGURE B.4: Correlation between the proxies for service quality.

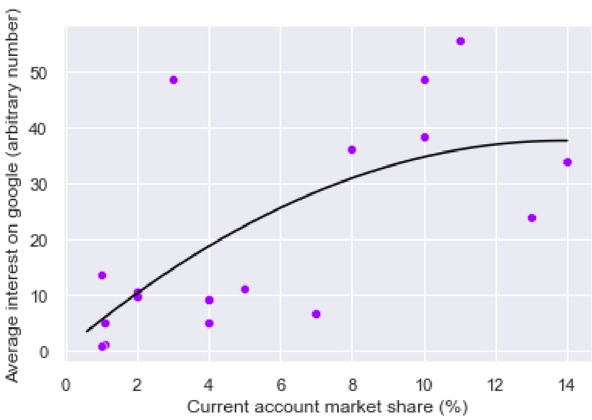


FIGURE B.5: Correlation between current account market share and Google trends between April 2021-2022.

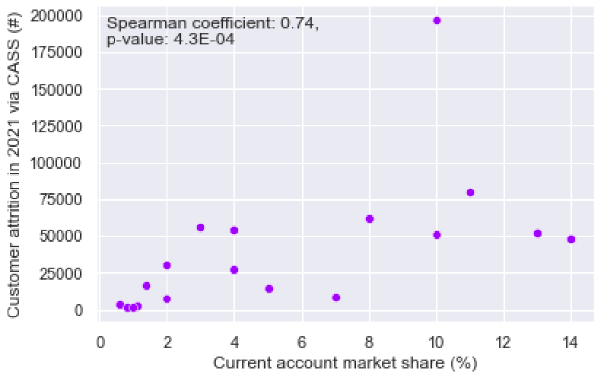


FIGURE B.6: Correlation between current account market share and the total customer attrition in 2021.

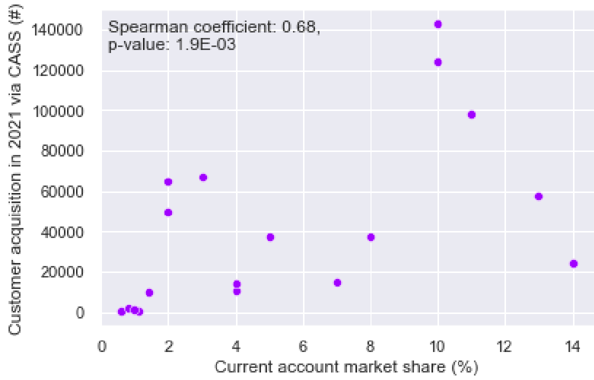


FIGURE B.7: Correlation between current account market share and the total customer acquisition in 2021.

PCA per Capita	a	b	c
1.9	-1.339e4	6.330e5	9.991e7
2.0	-8.833e3	6.778e5	9.995e7
2.1	-3.337e3	7.227e5	9.998e7

TABLE B.2: Resulting coefficients of fitted second-order polynomial curve (see eq. 4.3).

Yearly switches	a	b
3 million	0	0.75e6
4 million	8.9e3	0.75e6
8 million	4.4e4	0.75e6

TABLE B.3: Resulting coefficients of fitted first-order polynomial curve (see eq. 4.5).

B.3 Model inputs

bank	category	n customers	purpose driven	sustainability1	sustainability2	digital1	digital2	price1	price2	service1	service2
A	mid tier	600000	no	59.99	14.5	3.4	59	0	38		44
B	mid tier	1100000	no	54.05	20.8	2.4	58	0	53		53
C	big 4	7000000	no	50.44	20.6	4.1	77	0	57	64	60
D	big 4	14000000	no	43.08	17.3	4.3	79	150	67	65	64
E	mid tier	1400000	yes		9.2		60	20	52	70	52
F	mid tier	800000	no	45.72	24.1	3.6	75	150	60		59
G	big 4	1000000	no	46.04	19.3		81	0	73	82	79
H	big 4	3000000	no	50.44	20.6	4.7	79	0	59	67	62
I	big 4	10000000	no	46.04	19.3	3.6	73	150	58	57	57
J	big 4	13000000	no	50.44	20.6	3.2	77	125	65	66	62
K	mid tier	1100000	no	45.93		4.8	78	0	72	77	74
L	digital challenger	5000000	yes	66		4.4	85	5	66	83	80
M	scale challenger	10000000	yes		13.0		79	125	56	75	68
N	big 4	8000000	no	49.94	17.0	4.2	74	0	46	67	57
O	big 4	4000000	no	49.94	17.0	3.6	68	0	49	56	48
P	scale challenger	11000000	no	64.72	21.8	4.5	77	0	58	66	56
Q	digital challenger	2000000	yes	66		4.6	86	0	68	85	81
R	scale challenger	4000000	no	49.73	36.8	4.1	62	0	51	59	49
S	big 4	1000000	no	49.94	17.0	4.5	77	20	58		58
T	scale challenger	2000000	no	50.28	25.7		61	20	52	63	49

Table B.4: Model input data

B.4 Supplemental figures with model outcomes

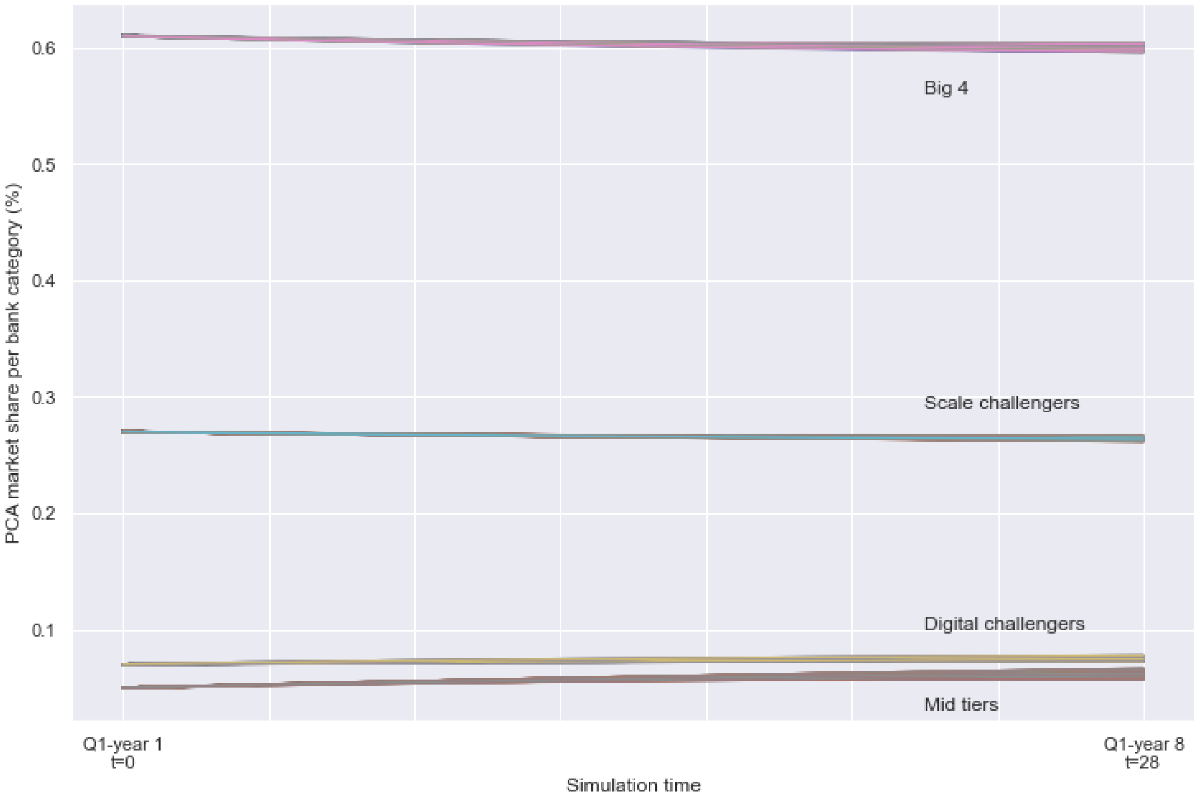


FIGURE B.8: PCA market share dynamics per bank category as generated by the open explorations of 400 scenarios with 30 repetitions each.

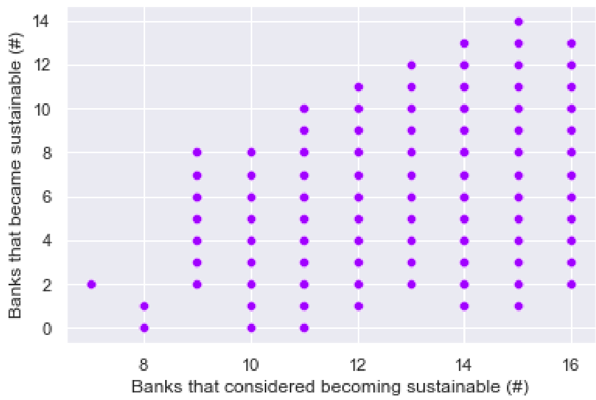


FIGURE B.9: Comparison of the number of banks that considered adopting a sustainable business model and the number of banks that decided to do so during the simulation.

TABLE B.5: Variable values per scenario.

Variable	Best case scenario	Second-best case scenario	Third-best case scenario	Worst case scenario	Second-worst case scenario	Third-worst case scenario
acq_digi	0.557953	0.239285	0.328163	0.074145	0.415127	0.360600

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Variable	**Best case scenario**	**Second-best case scenario**	**Third-best case scenario**	**Worst case scenario**	**Second-worst case scenario**	**Third-worst case scenario**
acq_price	0.033551	0.000805	0.057271	0.440066	0.194218	0.356784
acq_ser	0.405707	0.418929	0.350623	0.004653	0.000528	0.015399
acq_sus	0.002789	0.340981	0.263942	0.481136	0.390127	0.267217
adapter	4.000000	4.000000	1.000000	3.000000	4.000000	3.000000
copy	2.000000	3.000000	4.000000	5.000000	1.000000	1.000000
implementation duration	7.843192	6.462624	7.394314	5.703412	7.634404	7.827413
majority	4.000000	1.000000	5.000000	3.000000	3.000000	2.000000
nothing	3.000000	3.000000	2.000000	0.000000	6.000000	3.000000
pca_per_capita	1.902522	1.901295	1.904999	2.022496	2.084903	2.094401
speed	3.000000	3.000000	3.000000	1.000000	0.000000	5.000000
switches	1.942963	1.455960	1.558385	1.084828	0.947174	0.987129
threshold	0.000000	2.000000	1.000000	4.000000	2.000000	2.000000

Appendix C

Simulation model assumptions

In this Appendix, we discuss the implications of the model assumptions on the model validity. To this end, we first address the assumptions that were made on model input variables and second the assumptions on the model structure.

C.1 Estimations of model variables

C.1.1 Assumptions for the current market share per PCA provider

The initialization of the model required the number of customers per bank as an input variable. As such, we needed quantities for the current number of customers per bank. Due to lacking data sources, we estimated these quantities – which is extensively reported upon in section B.1 - using the following assumptions:

- The total market share of the big 4 banks as reported in sources can be distributed among its subsidiaries using the "consumer deposit" volumes that are reported in the annual reports of these banks. This assumption also applies to the mid tier category.
- The market share of the digital challengers can be distributed using the customer volumes that they reported in their annual reports, as both starling and Monzo have similar customers and similar services.

As both these assumptions are based on the advice of Expert 1, we argue that they are valid.

C.1.2 Assumptions on the proxies for the bank features

We quantified each bank feature using proxies using the following assumptions:

- Consumer choice of bank behavior can be represented by four different variables: sustainability, digital, price, and service.'
- Both ESG scores from Arabesque and ESG risks from Sustainalytics sufficiently represent the sustainability of a bank.

  Sustainability proxies reported per banking group can be generalized to all subsidiaries within the banking group.

  Digital challengers that are not included in the proxy datasets for the sustainability bank features can be assigned relatively high ESG scores Expert 1. Specifically, the environmental score is >70 given, the governance score is among the top performers, and the society score is lower than average.
- The combination of Google Play Store Ratings and a consumer survey sufficiently represent the digital capacities of a bank.
- The combination of switching incentives and a consumer survey sufficiently represent the price attraction of a bank.
- Two consumer surveys sufficiently represent the quality of service of a bank.
- The bank feature weights are $\mathbf{w_{attrition}} = [0.1, 0.1, 0.1, 0.7]$ and $\mathbf{w_{acqusition}} = [0.2, 0.3, 0.3, 0.2]$.

It must be noted that the selection of the proxies does not necessary represents the real-world. Towards ESG reporting, for instance, it is known that the rising data and compliance expenditures disproportionately affect smaller banks *"that are not as well-equipped with sophisticated corporate social responsibility (CSR) or sustainability departments"* (Arabesque, 2021). As such, larger banks might not be operating more sustainable than their smaller counterparts, but simply report in a manner that results in getting relatively better ESG scores. Consequently, there are multiple critical notes about greenwashing, saying that some "sustainability" efforts simply fall under the marketing umbrella to appease consumers and investors. Indeed, *in July 2021, the International Organization of Securities Commissions (IOSCO) found little clarity, alignment, or transparency in methodologies for rating of ESG funds. IOSCO also noted potential conflict of interest where consulting companies provided ESG services to companies but also produced ratings or data products incorporating the same companies* (Deloitte, 2022; IOSCO, 2021). This is also reflected in our observation that the Arabesque ESG scores and the Sustainalytics ESK risk are not correlated (see Figure B.1). While the current proxies for the sustainability of a bank are thus the best available, they are flawed. It will require capacity-building and technology to build a better functioning sustainability data landscape that also tackles concerns of ‘greenwashing’ and misrepresentation of a company’s sustainability credentials.

Similarly, one might question why Google Play Store ratings were used instead of Apple Store ratings, whether different survey providers might have more accurate insights, etc., but we cannot conclude that one proxy is more suited than the other. We simply selected those proxies that reported on most of the banks under study, thereby preferring consistency in reporting over all the banks than quality reporting on a few banks. One might conduct a sensitivity analysis using different initial values for the bank features to gain insights if the initial proxy values have a significant influence on the model outcomes, but due to time constraints, we did no such thing.

C.1.3 Assumptions for market growth forecasting and future switching volumes

The model relies on the exogenously modeled PCA market growth, as and such, we estimated this growth with the use of Expert 2. Specifically, the following assumptions were made:

- The net market growth represents the total number of consumers available for acquisition, besides consumers that seek to switch their PCA provider. Customers closing accounts are thus not included.
- There is an inherent difference between going from one PCA to two PCAs, and going from two PCAs to three or more PCAs, with the latter being less attractive to consumers.
- Population growth in the coming decade is small (3.2%) and mostly driven by immigrants, which do not have multiple PCAs in the UK (Office of National Statistics, 2021).
- The PCA market growth will impede with a logarithmic curve and result in 2.0 PCA per capita at the end of the simulation time (uncertainty interval [1.9, 2.1]).

The model also relies on the exogenously modeled switching volumes, as and such, we estimated these volumes with the use of Expert 2. Specifically, the following assumptions were made:

- There is no influence of Brexit on historical switching volumes.
- The historical switching volumes as reported by CASS are three times too low, i.e. the historical yearly switching volume is c.3m instead of the c.1m as reported by CASS.
- Consumer surveys do not reliable report on the historical switching volumes and should as such not be considered.
- An upswing in the reported intention to switch PCA provider in consumer surveys is a reliable indicator of a potential increase in future switching volumes.
- Gen Z will switching their PCA provider more, and as such, their influence on switching volumes will increase.
- There will be an increase in the switching volumes as the upswing in PCA market growth stagnates.

- Open banking will not increase switching volumes within the simulation time.
- There will not be an increase in switching volumes as CASS gets more common / easier / more trusted.
- The future switching volumes will increase with a linear curve and result in 1m switches per quarter at the end of the simulation time (uncertainty interval [0.75m, 2m]).

As all the above assumptions were either validated by or based on the advice of Expert 2, we argue that they are valid. In addition, as we acknowledge the uncertainties in the predictions by sampling them using EMA, the implications of inaccurate predictions are effectively mitigated.

C.1.4 Assumptions on the control variables

- Google trends are a result of the user's search, which were guided by advertisements and people talking about the company/product. We can thus deduce the Google Trends to be proportional to the money a company spends on advertising the product and, by implication, the amount of promotion that company receives.

This assumption has been validated during the Feedback Panel.

C.2 Model structure assumptions

C.2.1 Assumptions for scaling the bank feature scores

In accordance with exogenous market trends and the endogenous decision-making of banks during the simulations, we scaled the bank feature scores using the following assumptions:

- If a bank decides to adopt a sustainable business model, its sustainability feature score linearly increased to a random value drawn from a Beta(6, 3) distribution over the duration of the implementation period.
- The digital feature score of all banks in the simulation increased at every time step to the highest value among 28 samples drawn from a Uniform(0, 1) distribution, and the step size of the increase per simulation time step is given by the interval between the remaining 27 samples in ascending order.
- The price feature score is determined stochastically using a Markov chain with the following transition matrix (first row and column indicate the monetary incentive in pounds):

$$
\begin{array}{r}
\\ 0: \\ 5: \\ 20: \\ 125: \\ 150
\end{array}
\begin{array}{c}
\begin{array}{ccccc} 0 & 5 & 20 & 125 & 150 \end{array} \\
\begin{bmatrix}
0.5 & 0.2 & 0.1 & 0.1 & 0.1 \\
0.7 & 0.3 & 0 & 0 & 0 \\
0.7 & 0 & 0.3 & 0 & 0 \\
0.8 & 0 & 0 & 0.2 & 0 \\
0.8 & 0 & 0 & 0 & 0.2
\end{bmatrix}
\end{array}
$$

C.2.2 Assumptions on scheduling and temporal effects

- All consumers that switch their bank account, open a bank account at another retail bank in the same time step.
- Historical feature values are not relevant. That is, if bank A had a sustainable feature score of 0.8 for over a year, it will receive the same amount of influence from this feature as a Bank B that just reached a sustainable feature score of 0.8.
- The model included the twenty largest PCA providers, and, thereby, implicitly assumed that these players will remain the largest players in the future.

The assumption that an increase in a feature score immediately makes a bank more attractive to consumers could potentially project some inaccuracy into the model in terms of the final number of customers per bank as well as have temporal influences on when a bank may improve its customer acquisition, as potential delays in an entire are now not considered (Charan, 2020). One approach to capturing these latter carry-over effects is the use of stock variables. These variables implicitly distribute the amount of customer increase over several periods. In addition, a remedy to the continuous increase in attractivity for a bank if its feature score is increased could be to use a certain threshold to determine if customers find an attribute 'sufficient'.

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