Modeling the Impact of Big Data Analysis Investments on the Dynamics of Customer Acquisition

A Case Study of Telecommunication Sector in the United States

By

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ABSTRACT

In the age of data explosion, many firms are heavily investing in big data and big data analytics (BDA) without being able to anticipate how much value they will receive. Thus, there is a growing body of research that has been focusing on the impact of big data and BDA investments on firm performance. Nevertheless, most of these studies use self-reported data and none of them has addressed the dynamics in the firm outcomes as well as the continuous feedback processes between BDA investment, firm performance, and other intermediate variables. In this thesis, I collected data about two telecommunication firms in the U.S., namely T-Mobile and Verizon, to build up a system dynamics model that helps to answer two research questions that have not been properly investigated hitherto: 1) How do BDA investments dynamically influence firm performance? and 2) Which policies can help large and small firms to enhance the outcomes of their BDA investments? My simulation results reveal that when the industry develops in favor of BDA activities (i.e., lower data acquisition and data storage costs, more data generated by customers), small firms will be put at a disadvantage. In contrast, large firms with larger customer bases will be able to exploit their economies of scale in BDA investments to quickly increase their market share and gain higher profits. Thus, large firms are advised to increase their investments in BDA and data acquisition, in addition to increase their data volume more quickly even at the cost of lower data quality. As an increase in data volume will typically lead to a decrease in data storage cost, this policy will help large firms effectively increase their total number of customers, which will lead to a further decrease in the data acquisition cost, resulting in higher firm revenues and firm profits. Small firms, instead, are advised to sacrifice their profits for market share. Specifically, they should invest more heavily than large firms to lift the volume of their data up to the point that it can nullify the cost advantage of large firms. It is unclear that, though, whether small firms can survive when making such a big trade-off. Future research might explore whether the intervention from governments might help resolve this inequality between small and large firms.

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BDA: Big Data Analytics

CLD: Causal Loop Diagram

SD: System Dynamics

SFD: Stock and Flow Diagram

Chapter 1: Introduction

1.1 Background Information

We are living in the age of data explosion. For example, we are receiving billions of emails every week, sending half a billion of tweets every day, posting nearly 300,000 Facebook status updates every minute, and spending many hours staying online or talking over the phones (Marr, 2015). With the rapid development of digitalization and the widespread usage of internet-of-things devices around the world, firms are now able to follow these digital traces of customers to anywhere, at any moment, leading to a massive amount of data collected about customers in recent years (Rust, 2020). Indeed, Facebook, for instance, collects more than 500 terabytes of customer data on a daily basis, and Netflix owns millions of real-time data points from its online movie viewers (Xu, Frankwick, & Ramirez, 2016).

It is believed that these large customer databases, which are also known as “big data,” provide firms with many radical opportunities to gain important insights about customers and then convert those insights into informed market decisions and a competitive edge (Erevelles, Fukawa, & Swayne, 2016; Rust, 2020). Consequently, a growing number of businesses has been investing a substantial amount of money in big data analytics (BDA) in an attempt to take full advantage of their large amount of customer information. For example, the Oversea-Chinese Banking Corporation managed to increase the overall conversion rates by 45% after investing in advanced analytics (Turner, Schroeck, & Shockley, 2013), while AT&T exploits their data collection of 30 billion data points per hour to optimize resource allocation and enhance customer experience (King, 2014). Furthermore, results from a study conducted by Accenture and General Electric show that almost 90% of surveyed firms believe that they must invest in BDA to secure their market shares (Aydiner, Tatoglu, Bayraktar, Zaim, & Delen, 2019). However, big data investment does not always lead to higher business value, and previous research has found that the relationship between BDA investments and firm performance is not necessarily being positive (e.g., Wamba et al., 2017).

In fact, our understanding of whether, why, and how BDA investments would lead to increase in firms’ business value is very limited (e.g., Aydiner et al., 2019; Côrte-Real, Ruivo, Oliveira, & Popovič, 2019; Erevelles et al., 2016). Indeed, previous research that has empirically investigated the association between BDA and firm performance using real data is really scarce (J. Q. Dong & Yang, 2020), while a worldwide survey shows that half of the firms that are actually investing in BDA do not experience any benefit of it (Côrte-Real et al., 2019). In a similar vein, while 75% of more than 400 Gartner research circle members indicated that they spent money or planned to spend money on big data analytics in the next two years, about 40% of them were not able to anticipate whether these investments would result in any positive business value (Lam, Sleep, Hennig-Thurau, Sridhar, & Saboo, 2016). This raises at least two challenging practical questions for firms to answer: (1) How do firms' investments in BDA dynamically influence their performance? and (2) How do the nature of the competition (e.g., large vs. small firms) and other market characteristics affect the effectiveness of the firms' policies on BDA investments? In this thesis, I aim to tackle these issues by building a system dynamics (SD) model that helps explain not only the impacts of BDA investments on the dynamics of firm performance such as market share and firm profit, but also how different market scenarios and investment policies would dynamically influence the performance of the small versus large firms over time. The findings will provide managers with relevant and important insights into BDA investment decision-making.

1.2 Problem Formulation

1.2.1 Business Value of BDA Investments

According to Verhoef, Kooge, and Walk (2016), firms invest in BDA for two different purposes, namely gaining customer insights and developing models to improve decision-making. As such, BDA investments can be used to create business value in three major ways (Verhoef et al., 2016). First, firms might be able to make better marketing budget allocation decisions. For instance, firms might decide to invest more heavily in social media marketing to recruit new customers if results from their data analytics show that most of their prospective customers are highly engaged in social media activities. Indeed, Saboo, Kumar, and Park (2016) find that firms can improve their sales per customer by more than 17% just by reallocating their marketing resources based on insights from utilizing large volumes of customer transaction data.

Second, firms could improve the effectiveness of their marketing actions and campaigns with results from BDA activities. In particular, people tend to prefer things that can meet their personal needs or unique requirements (Rust, 2020), and feel more satisfied when receiving personalized offers (e.g., Yoo & Park, 2016). In other words, advanced analytics could help firms fully tailor their marketing messages to each customer (e.g., personalized direct email marketing), which in turn makes marketing communication more effective.

Finally, with deeper customer insights, firms could identify the extra features, functionalities, or extra services that customers desire. For example, Liu, Soroka, Han, Jian, and Tang (2020) argue that online opinions posted by customers (e.g., online reviews) are a valuable source of information for product designers and for design innovation. As such, results from BDA activities could help firms improve quality of products and services.

Previous studies, however, has disregarded the dynamics in the relationships between BDA investments, marketing effectiveness, and customer acquisition. More specifically, firms first invest in BDA to increase their knowledge of customers and their behaviors. However, as firms' understanding of customer insights increases, extra money spent on BDA activities becomes less productive. In other words, at some level, the extra investments in BDA activities only provide firms with little extra knowledge of customers, implying a diminishing trend of return on investment. Similarly, the enhanced knowledge of customers helps firms personalize their marketing content better, leading to an increase in the effectiveness of direct marketing activities. However, when the benefit of personalization increases, the positive effect of personalization on customer responsiveness is getting smaller, indicating another diminishing trend of returns. To the best of my knowledge, empirical research addressing the dynamic impact of BDA investments on marketing effectiveness and customer outcomes using real financial data is absent, leading to potential biases in measuring performance of investments, especially in relationship marketing (e.g., Ambler & Roberts, 2008; Hibbard, Brunel, Dant, & Iacobucci, 2001).

1.2.2 BDA Investment Strategies for Firms with Small vs. Large Customer Base

Previous research has mostly relied on the use of self-reported measures (e.g., survey) to investigate the effects of BDA adoption on firm performance (e.g., Aydiner et al., 2019; Côrte-Real et al., 2019; J. Q. Dong & Yang, 2020). While the advantage of self-reported measures is that we are able to capture direct observations of BDA usage through the managers' lens and the convenience of the data collection process, these studies are limited in offering strong evidence for the causal effects of BDA usage on firm outcomes. Importantly, these survey-based studies provide limited information for researchers and practitioners who are interested in market simulation to analyze and predict optimal policies for firms, especially when different firm and market characteristics are changed simultaneously. For example, on the one hand, emerging evidence shows that, in the finance sector, small firms, who do not own a massive customer base and therefore have no access to a wealth of data, are struggling to grow, because investors are increasingly considering large firm with big data as a less risky bet (Begenau, Farboodi, & Veldkamp, 2018; Farboodi, 2018). On the other hand, other people claim that, in the age of big data, startups and small firms are having much bigger impact on the global economy, and opportunities for them are higher such that they can scale up their businesses much more quickly (e.g., Bradner, 2016). This raises an intriguing question to answer: What would be the best investment policy for small versus large firms to realize the benefits of big data? In this thesis, I therefore aim to explore different market scenarios to see how the size of the firm's customer base (i.e., large vs. small) affects the dynamic impacts of BDA investments on firm performance and propose policies that help enhance the benefits of BDA use.

1.3 Research Objective and Research Context

Based on the above discussion, this thesis aims to (1) model the impact of BDA investments on the firm' performance such as total number of customers and net profit given the relative size of the firm's customer base (i.e., small versus large), and (2) suggest investment policies that help firms exploit the benefits of big data and enhance firm outcomes (i.e., number of new customers and firm profit). As such, using literature on big data and business/marketing analytics, I develop a system dynamics (SD) model that represents the structure underlying the influence of BDA investments on firm performance. The simulation results are expected to enhance our understanding of when and how big data and BDA would generate positive business values for firms, given their relative size. In addition, the model would serve as a useful tool for policy makers and researchers to analyze the effectiveness of different BDA investment decisions under different market situations and thus identify the optimal policies for small versus large firms to take full advantage of big data, the "new oil" of this century.

In this thesis, I focus on the telecommunications sector in which the above research questions are particularly important. Indeed, customers are providing telecommunication firms with an increasingly massive amount of data such as call detail records, text messages, mobile browsing history, or billing information. For example, in the UK, people using smartphones tend to make about 220 tasks and spend more than three hours on our phones every day (MacNaught, 2014). Consequently, telecom firms are investing heavily in big data analytics to understand factors driving customer behaviors and use these insights to develop better marketing activities to convert customers to a long-term relationship (Wassouf, Alkhatib, Salloum, & Balloul, 2020). In particular, according to Bughin (2016b), 30% of telecom firms has adopted BDA. Among these firms, more than 75% have established big data projects in sales and marketing areas, more than 50% have adopted BDA for customer service, and about 35% have used big data to achieve competitive insights. Hence, with access to extensive bits of data, in addition to a strong demand for technological innovation, big data has a huge potential to provide firms with benefits in the telecom industry (Bughin, 2016a; Tambe, 2014), implying that understanding the effectiveness of BDA investments is important for firms in this industry.

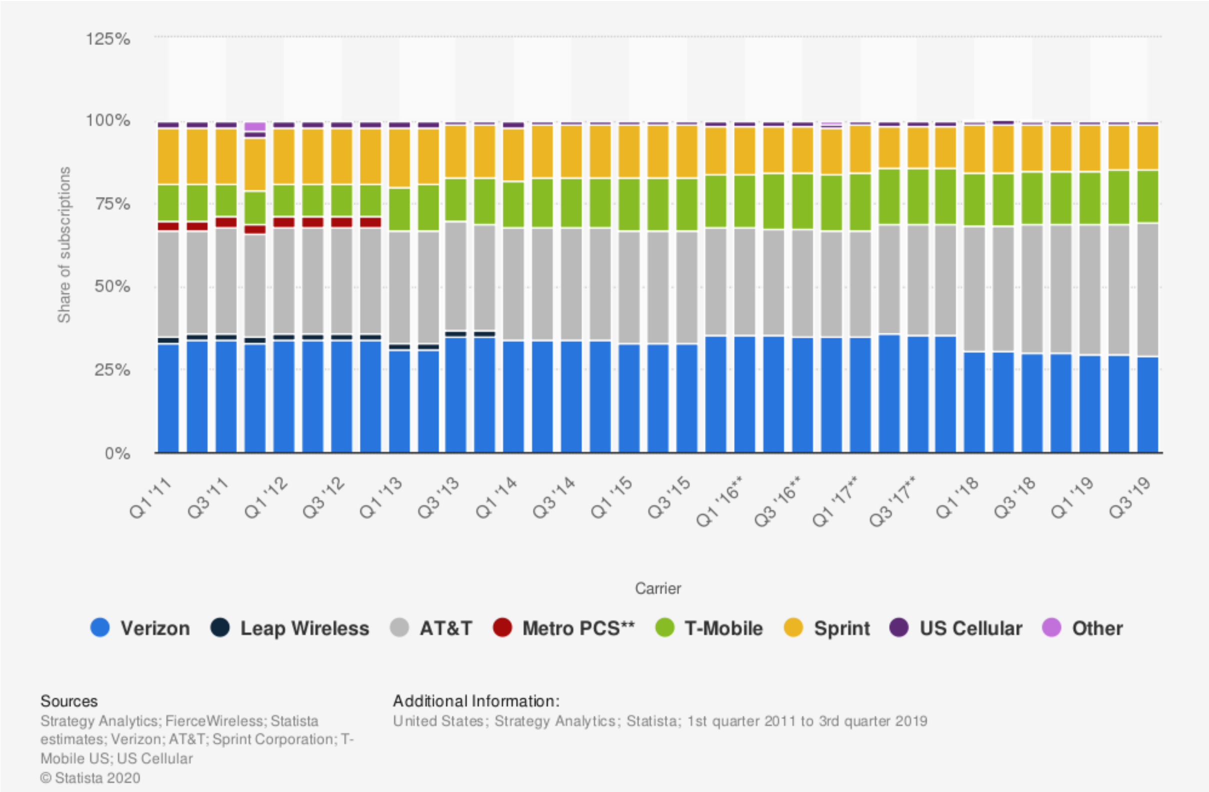


Figure 1. Market Share of the Telecommunications Sector in the U.S. (2011-2019) (adapted from FierceWireless and Statista (2019))

Furthermore, to simplify the market structure, I simulate a dynamic market with only two firms competing against each other. The first chosen one is Verizon who owns the biggest market share of about 30% and is considered a large firm in the industry. The second one is T-Mobile who owns a smaller market share of about 15% and is considered a small firm. As seen in Figure 1, while the market share of Verizon is slightly decreasing, T-Mobile's market share seems to be slightly increasing.

1.4 Research Questions and Research Context

The above-mentioned reasoning leads to two main research questions that can be defined as follows:

1) How do BDA investments dynamically influence firm performance (i.e., total number of customers, firm revenue, and firm profit)?
2) Which policies can help large and small firms to enhance the outcomes of their BDA investments?

Reference modes were developed from historical data of firms regarding number of total customers and net profit (see Figure 2). In this thesis, I will answer the first research question by developing a SD model that could closely replicate the patterns of the reference modes (see Chapter 5). After that, the second question is answered by proposing investment policies that help firms obtain better outcomes (e.g., number of total customers and firm profit) than those in the reference mode (see Chapter 8).

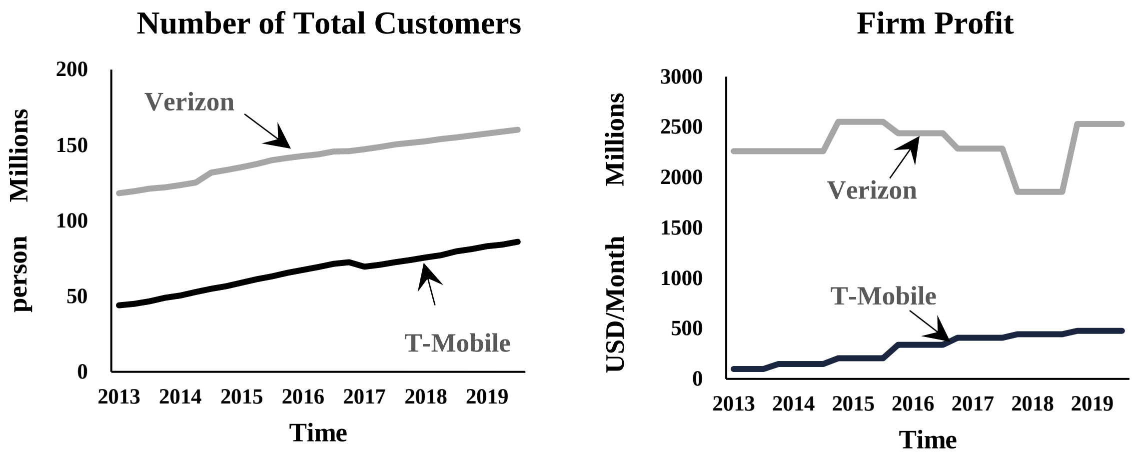


Figure 2. Reference Mode of Firm Performance of T-Mobile and Verizon

1.5 Thesis Outline

This thesis contains 9 chapters. Chapter 1 introduces the main topic of the thesis and why it is considered important and relevant to the field. In Chapter 2, I review the current literature and existing theories that are relevant to the development of my SD model. Chapter 3 explains why the system dynamics modeling method was chosen to answer the abovementioned research questions and describes the data collection process. Chapter 4 describes the main structure and major feedback processes of the SD model. Chapter 5 is used to describe the calibration of the model and the fit between the simulated and the actual behaviors. In Chapter 6, I show that the model is robust by presenting different structure and behavior validity tests. Chapter 7 reports several different hypothetic scenarios and the corresponding changes in model behaviors. In Chapter 8, I analyze the proposed policies and discuss the results. Finally, Chapter 9 is used to conclude the thesis with general discussion, limitations, and avenues for future research.

Chapter 2: Literature Review

In this chapter, I review the relevant literature that is used to develop my system dynamics model in Chapter 4. Specifically, this part describes the current literature on big data, BDA, and marketing literature on personalization, marketing responsiveness, and customer acquisition. The diagram of the model is presented at the end of this chapter.

2.1 Big Data and Its Characteristics

Customer data, which captures the raw information about customers such as characteristics or behaviors, has been around for decades but started first at an aggregate level, such as monthly or annually purchase amount (Verhoef et al., 2016). After many firms begun to invest in large customer databases in the 1990s, the amount of customer data ballooned, for example with detailed transaction records for millions of customers as well as their background information such as age, gender, or occupation (Rigby, Reichheld, & Schefter, 2002). Nowadays, customers' online activities can be recorded by firms every minute or even second, resulting in vast amount of data containing billions bit of observations, which is often considered as "big data".

One problem, however, is that a big data's definition based on data size alone can be quickly outdated. For example, a data warehouse containing 250 petabytes of data owned by Facebook in 2013 which was (and still is) considered impressive could become normal in ten years from now (Leetaru, 2019). Thus, big data is often defined using more general terms, such as "extremely large datasets, made up of structured and unstructured data that can be processed and analyzed to reveal patterns and trends" (Hazen, Boone, Ezell, & Jones-Farmer, 2014). Similarly, big data can also be referred to "a collection of large, heterogeneous and complex datasets that are difficult to process using conventional tools and applications" (Hallikainen, Savimäki, & Laukkanen, 2020). The consensus is that data volume (i.e., data size) is just one characteristic of big data, in addition to other aspects such as velocity (how quickly the data is generated and analyzed), variety (how many forms of data that were collected, e.g., structured vs. unstructured data), veracity (the quality of the data), and value (the importance, relevance, and completeness of the data), making up a set of five Vs that are typically considered as key characteristics of big data (e.g., Erevelles et al., 2016).

In this thesis, I adapted the conceptual framework proposed by Lam et al. (2016) to model the impact of big data on the firm's knowledge of customers. According to these authors, the conversion of big data to applicable knowledge is composed of two major parts: (1) converting big data availability to big data value and (2) converting big data value to knowledge. More specifically, big data availability, which involves big data volume, velocity, and variety, influences big data value through the quality of the data indicated by big data completeness and consistency (Lam et al., 2016). Building upon previous literature on data quality (Peltier, Zahay, & Lehmann, 2013), I decompose data quality into four primary areas including big data completeness, data accuracy, data consistency, and timeliness.

Specifically, big data completeness refers to the extent to which firms have sufficient information (regarding both breadth and depth) about the customers such that they could explain their behaviors in the past, the current, and predict them in the future (Lam et al., 2016). Big data accuracy, instead, refers to the extent to which the collected data might contain biases, missing values, duplication, or other inaccurate information. Similarly, big data consistency refers to the consistency in measurement of different variables in all the data sets, while timeliness refers to the accessibility and availability of data when the firm needs it (Peltier et al., 2013). For simplicity, I grouped data consistency and timeliness as one variable due to their similar evolvement caused by big data availability.

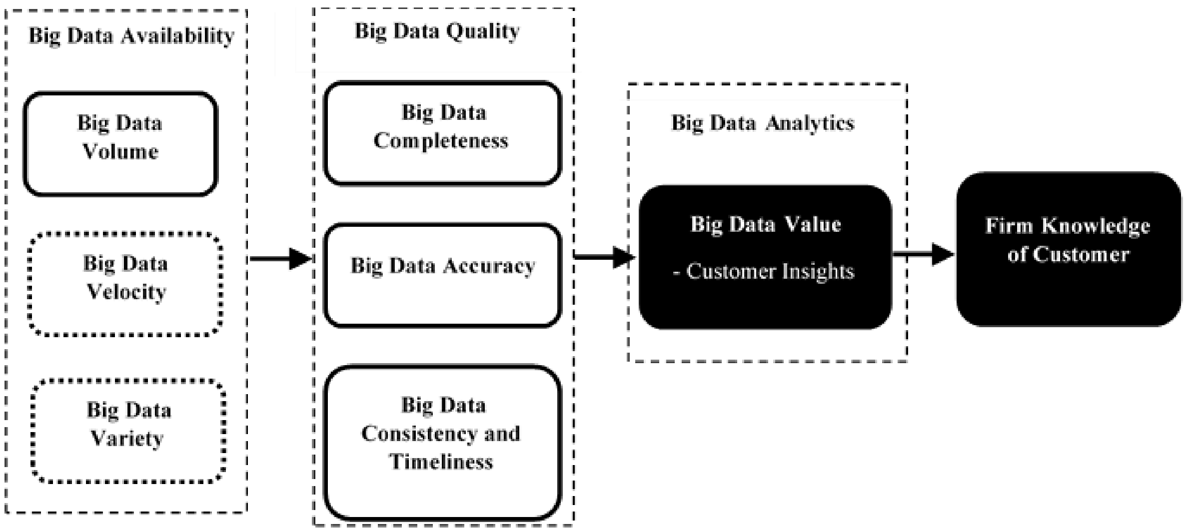


Figure 3. Knowledge Generated From Big Data (adapted from Lam et al. (2016)'s conceptual framework)

In addition, I chose to not include big data velocity and variety in my system dynamics model due to the unavailability of necessary data and information, as well as because these two dimensions of big data are mostly affected by the skills of employees (i.e., data scientists, data analysts) which are not the focus of this thesis. Big data quality is expected to be converted to big data value, which refers to actionable customer insights such as heterogeneous customer preference, or situational and psychological information related to customer behaviors (Lam et al., 2016). As suggested by Erevelles et al. (2016), big data value depends on firms' investment in big data analytics. Finally, these BDA activities converts the customer insights gained from big data to firms' knowledge of their customers that is now readily applied in marketing, sales, product design, or other frontline activities. Figure 3 illustrates these key processes in my model.

2.2 Big Data: Trade-off Between Quantity (Volume) and Quality

The trade-off between quantity and quality exists in many aspects of our lives. For example, a person might be able to do many tasks in a day but at low quality, while another one might do a few tasks but at high quality. This is because there are limits to our working productivity and we must be strategic when everything cannot be done. In big data collection, there is no exception. Indeed, a firm might choose to focus on big data volume (quantity), so a lot of data are collected but at reduced quality. In contrast, another firm might choose to focus on data quality, so not all information is collected but the collected data are at very high quality. In fact, customer data are now generated at an amazing pace, so data quantity or data availability is usually not a problem to firms anymore (Panoho, 2019). However, as big data analytics such as machine learning algorithms are known for being "hungry" for data, such that they typically require millions of observations to perform well, big data users tend to overfocus on data quantity and disregard the role of data quality (Obermeyer & Emanuel, 2016). Following previous research (Hazen et al., 2014), I assume that when firms over-invest in big data volume, data completeness will increase due to more information is collected but data accuracy will decrease as firms will get more data errors. The collected data might eventually become less consistent (lower data consistency) and the accurate data might become less accessible (lower timeliness).

2.3 Impact of Big Data Analytics

Big data analytics (BDA), in general, can be defined as a collection of techniques and technologies that firms use to analyze big and complex data in order to enhance firm performance in different ways (Chen, Chiang, & Storey, 2012; Côrte-Real et al., 2019). Existing evidence from previous research has demonstrated that BDA, and customer analytics in particular, can significantly improve firm performance (Côrte-Real et al., 2019; Wamba et al., 2017). Following Verhoef et al. (2016), I propose that firms' knowledge of customers (obtained through BDA) positively influences firm performance in three major ways, namely through (1) segmentation and targeting, (2) personalization in direct marketing, and (3) product quality.

2.3.1 Segmentation and Targeting

Segmentation and targeting, a core element in a marketing strategy, is often referred to as the firm' efforts to identify which customers it will serve. According to Kotler and Armstrong (2017), it takes a lot of firms' resources to offer customers with high quality services and firms are often not able to do so with all of their customers. Instead, firms often strategically choose to focus most of their resources on a smaller number of customers, which is also known as a target market, and allocate less resources on other customers. Thus, a good segmentation and targeting strategy is expected to result in a significant increase in firm revenue. For example, after three years adopting a new strategy of segmentation, a telecom firm from the Eastern European market was able to observe significant improvement in return of investment and revenue from all identified segments (Dibb, Rushmer, & Stern, 2001).

However, "delivering the right message to the right customer at the right time" (Bradlow, Gangwar, Kopalle, & Voleti, 2017, p. 81) is typically not an easy task to any firm. In fact, to divide a whole market into different unique segments of customers, and evaluate which segment is more attractive than the other, firms cannot rely on a single piece of information from customers, but rather a combination of factors regarding of their demographics, psychographics, geography, and behavioral patterns, segmentation and targeting require significant knowledge in terms of customer insights (Kotler & Armstrong, 2017). Thus, many firms are investing heavily in big data and BDA to improve their outcomes in market segmentation and targeting (Verhoef et al., 2016). For example, previous research has demonstrated that understanding customers' transactional behavior might help increase the click-through-rate of advertising by as high as 670% (Yan et al., 2009). Similarly, Nair, Misra, IV, Mishra, and Acharya (2017) use customers' marketing responsiveness information obtained from big data analytics of a firm to optimize its segmentation and targeting. Their results suggest that, by allocating more money to more profitable customers, the firm's profit was increased up to 3.3 dollars per customer. Hence, in this thesis, I expect that the firm's knowledge gained from BDA investments would help identify the right target market with higher marketing responsiveness and minimize the targeting error such that less marketing effort would be spent on people with no interest in making a purchase or becoming a subscriber. More specifically, as shown in Figure 4, I suppose that the firm's knowledge of customers would reduce the missed target customers part and minimize the number of customers who would be mistakenly targeted. While firms lose money when failing to target the right potential customers (i.e., so they are not aware of the product to buy/subscribe), they also lose money by targeting the wrong people (i.e., who are not interested in making a purchase/transaction).

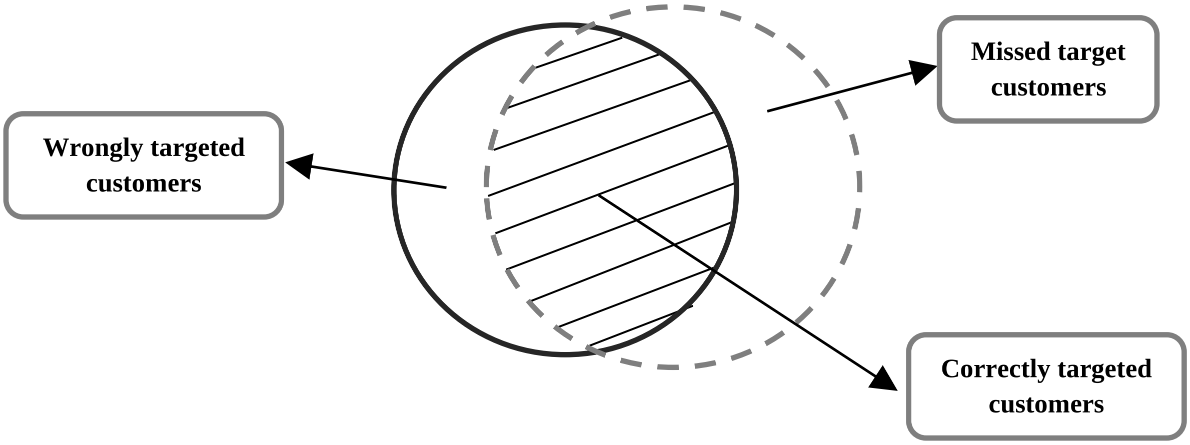


Figure 4. Actual Target Customers (Solid Circle Line) Versus Desired Target Customers (Dashed Circle Line)

2.3.2 Personalization in Direct marketing

Personalization, an effective way to address an individual customer's needs, has been applied in direct marketing efforts since the 1870s (Vesanen, 2007). Following Montgomery and Smith (2009), in the context of this thesis, I define personalization as the adaptation of direct marketing contents for the customer using knowledge that has been resulted from BDA activities. Previous evidence has demonstrated that personalization increases customers' perception of internal control (e.g. Surprenant & Solomon, 1987). The greater perceived control over the outcome, even though it might be just an illusion (Langer, 1975), can then positively influence customer behaviors. In the past days, personalization is considered an expensive way to increase customer responsiveness as it was usually done on a case by case basis, leading to a typical trade-off for service firms between a high quality, personalization strategy and a low cost, standardization strategy (Rust, 2020). Nowadays, personalized marketing however is automated by machine learning and deep learning (artificial intelligence) algorithms using big data, meaning that firms can adopt the personalization strategy at significantly lower costs. For example, by analyzing users' listening preferences, Spotify was able to provide their users personalized playlists and artist recommendations, which have been demonstrated to increase the listening duration and the number of songs listened to (Chung, Rust, & Wedel, 2009; Misiak, 2019). Similarly, when privacy concern is controlled, Facebook users are also twice as likely to click on personalized advertising compared to non-personalized one (Tucker, 2013). Thus, in this thesis, I assume that the firm's knowledge gained from BDA activities could help increase the effectiveness of direct marketing contacts through personalization, such that targeted people are more likely to respond to the firm's advertising and then become customers (subscribers).

2.3.3 Product quality

Previous research has suggested that product attractiveness as an important determinant of customer acquisition (e.g., Paich & Sterman, 1993; John D. Sterman, Repenning, & Kofman, 1997; Struben & Sterman, 2008). Key factors that influence product attractiveness include price, product availability, marketing expenditure, and product quality (John D. Sterman, Henderson, Beinhocker, & Newman, 2007; Struben & Sterman, 2008). Product quality, in its turn, is affected by the quality of its service, hardware, and software, according to the TL 9000 telecommunication standard (DNV GL Group). According to Shollo and Galliers (2016), product quality would be significantly benefited by big data that is pushing us to the next frontier for innovation. Indeed, BDA would enable firms to extract useful insights from a massive amount of data regarding users' product evaluations, recommendations, and product use, to quickly develop a new version of the existing product with successful modification (Xu et al., 2016). For example, Netflix uses advanced analytics on its big data of subscribers' preferences and habits to predict which movies to license and whether it is worthy to invest in new shows or new movies, leading to enhanced product quality and subsequently significant growth in its subscriber base (Yu, 2019). Thus, I suggest that BDA investments would increase the firm's knowledge of customers, that will be used to improve product quality and product attractiveness subsequently.

Chapter 3: Methodology

3.1 Research strategy

In this master thesis, the chosen methodology to study the proposed research questions is system dynamics modeling. System dynamics modeling was starting in the 1950s by Jay W. Forrester (Forrester, 1958) and quickly became a strong methodology to analyze complex systems (John D. Sterman, 1994), with applications in many areas including firm growth (e.g., Forrester, 1964), management and decision making (e.g., John D. Sterman, 1989; John D. Sterman, 1992), fossil fuel resources (e.g., Davidsen, Sterman, & Richardson, 1990; J. Sterman, G. Richardson, & P. Davidsen, 1988), transportation (e.g., Struben & Sterman, 2008), healthcare (e.g., Homer, Hirsch, Minniti, & Pierson, 2004; Hovmand, 2014), (generic) marketing (e.g., Nicholson & Kaiser, 2008), and finance (e.g., Azeem Qureshi, 2007), just to name a few.

For the purpose of this thesis, system dynamics outperforms other methodologies (e.g., econometric modelling) in two major ways. First, system dynamics modeling is better than other common modelling methods (e.g., time series modeling) in throwing new light on the feedback in a causal chain of variables (Rand, Rust, & Kim, 2018). In particular, system dynamics approach allows its users to model a system of differential equations through a set of stocks and flows (Saleh, Oliva, Kampmann, & Davidsen, 2010). Hence, by its design, this method is useful to understand the dynamics and complex interdependence among the elements of a system (Rand et al., 2018; John D. Sterman, 2001). In this study, such complexity and feedback processes play an important role in the system. For example, how much a firm decides to invest in BDA depends on firm revenue. These BDA investments then affect the firm's knowledge related to customer insights. This learning process will result in enhancement in marketing effectiveness, leading to growth in the firm's customer base and revenue which in turn would foster BDA investments once again. These kinds of problem can be best studied by analyzing the flows of the system (Rand et al., 2018), making system dynamics the most suitable method for my thesis.

Second, system dynamics allow us to conduct a series of trial-and-error simulations in which different value of parameters can be tested and the feedback structure can be changed in an attempt to explore the structural relationship between system elements and to discover the most feasible and profitable policy options (Saleh et al., 2010; J. D. Sterman, G. P. Richardson, & P. Davidsen, 1988). As the system behavior (e.g., customer acquisition in my thesis) is strongly dependent on its structure composed of many different causal loops and other effect assumptions (Davidsen et al., 1990), system dynamic modeling is superior to other modeling techniques when our understanding of the system is still limited. Because studies on the impact of big data and BDA investments in firm performance are still in its infancy, using system dynamics modeling allows me to experiment with different model elements and learn more about the relevant complexities and feedback processes before advising firms on how to take full advantage of BDA investments.

To sum up, system dynamics modeling is considered an appropriate approach to achieve the research objective of this master thesis. In the next part, I will explain how the data collection process has been implemented in this thesis.

3.2 Data collection

To build and estimate the system dynamics model in this master thesis, we need inputs regarding: 1) the key variables in the model (in terms of stocks and flows); 2) the relationship between them (i.e., causal loops); 3) data (e.g., number of customers of the firm over time, etc.); and 4) effects (e.g., price elasticity of product attractiveness, effect of BDA investments on the firm's knowledge of customers, etc.). The data collection process in this thesis is composed of three major steps. First, I delved into the past literature to understand to what extent the problems formulated in this thesis have been examined by previous research and use that knowledge to build up my own system dynamics model. To perform a thorough and systematic search of literature, I followed Snyder (2019) and explored a comprehensive set of online databases including Google Scholar, EBSCO, Web of Science, and Science Direct, as well as the reference lists of the found papers, to try to as many as possible all the relevant and important studies. Based on previous literature in big data and BDA, in addition to my own understanding, I used a combination of different keywords such as: *Big Data*, *Big Data Analytics*, *Big Data Investments*, *Customer Analytics*, *Return on Investment in Big Data*, *Effect of Big Data*, *Effect of Big Data Analytics*, *Costs in Big Data Analytics*, *Big Data in Business*, *Big Data in Marketing*, and *Big Data and Firm Performance*. After quickly skimming all the found articles (i.e., their abstracts), irrelevant papers were excluded. The review of the remaining studies at this step was then used to construct the overall causal loop diagram (CLD) and the stock and flow diagram (SFD). All the data and effects were simulated to test if the system dynamics model could work and be ready to move on to the next step.

In the second step, I started collecting data used in the model. The system dynamics model developed in this thesis uses the competition between T-Mobile and Verizon Wireless, which are American telecommunications firms offering wireless products and services in the U.S., as a case study. The specific data about each firm and the whole market were mainly collected from their annual reports that are publicly available on their websites and online statistics portal such as Statista. Other variables such as effect of the firm's knowledge of customers on productivity of BDA or effect of direct marketing quality on customer responsiveness were collected from previous empirical studies. The real data was used to refine the model so it could be used to explain and predict the behavior of interest.

In the last step, intensive tests of model sensitivity and scenario analysis were performed. The literature was reviewed again not only to understand the findings but also to refine the model assumptions again if inconsistency or counterintuitive results were found. After the modeling process is completed, the model is described in Chapter 4, while Chapters 5, 6, 7, and 8 present the results.

Chapter 4: Model Description

4.1 Model Overview

This part describes the overview of the system dynamics model constructed in this thesis.

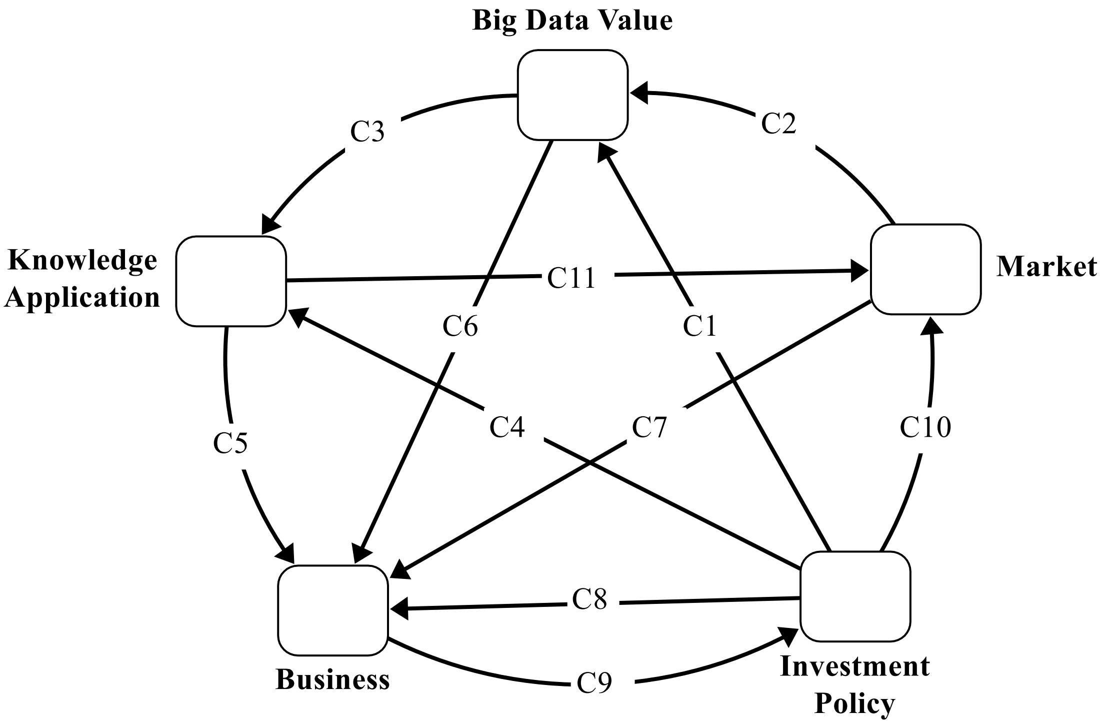


Figure 5. Overview of the Model

As shown in Figure 5, the model contains five main interconnected modules: Big Data Value, Knowledge Application, Market, Business, and Investment Policy. Information is sent and received through nine different connections (C1-C11). Table 1 gives a brief summary of all these elements.

Element	Information Sender	Information Receiver	Explanation
SECTOR			
1. Big Data Value	N/A	N/A	This sector illustrates the conversion of big data (e.g., big data volume and quality) to the firm's knowledge of customers

2. Knowledge Application	N/A	N/A	This sector illustrates how the firm's knowledge of customers are applied in and has impact on marketing, product development, and churn management
3. Market	N/A	N/A	This sector illustrates the effects of marketing and product attractiveness on the dynamics of customer acquisition, as well as on the growth of the total market over time
4. Business	N/A	N/A	This sector illustrates the dynamics in the revenue and costs of the firm
5. Investment Policy	N/A	N/A	This sector illustrates direct impact of different BDA investment policies used in this thesis
CONNECTOR			
C1	Investment Policy	Big Data Value	This connector illustrates how the firm's knowledge of customers is influenced by the firm's BDA investment policy
C2	Market	Big Data Value	This connector illustrates how the number of newly recruited customers is influenced by the firm's BDA investment policy
C3	Big Data Value	Knowledge Application	This connector illustrates how direct marketing effectiveness, product quality, and churn rate are influenced by the firm's knowledge of customers
C4	Investment Policy	Knowledge Application	This connector illustrates how the quality of direct marketing is influenced by the firm's BDA investment policy
C5	Knowledge Application	Business	This connector illustrates how firm costs are influenced by the extent to which the firm' knowledge of customers is applied in direct marketing
C6	Big Data Value	Business	This connector illustrates how firm costs are influenced by the firm's expenditure on increasing big data volume and/or quality

C7	Market	Business	This connector illustrates how firm revenue and costs are influenced by the firm's total number of customers
C8	Investment Policy	Business	This connector illustrates how firm costs are influenced by the firm's BDA investment policy
C9	Business	Investment Policy	This connector illustrates how the firm' BDA investment policy is influenced by firm revenue
C10	Investment Policy	Market	This connector illustrates how the number of targeted customers is influenced by the firm's BDA investment policy
C11	Knowledge Application	Market	This connector illustrates how the number of newly recruited customers is influenced by the extent to which the firm's knowledge of customers is applied to improve direct marketing effectiveness, product quality, and churn rate

Table 1. Summary of Model Overview Elements

4.2 Model Boundary and Time Horizon

Model boundary refers to the scope of the model (e.g., the selection of studied variables) while the time horizon of a model refers to the duration in which the model is simulated. According to J. Sterman (2000), selecting a reasonably broad model boundary and a reasonably long time horizon is one of the most important tasks in modeling the dynamics of a system. For example, too narrow model boundary would make the model less useful for managers or policy makers, while too broad boundary might lead to the inclusion of a long array of variables that requires an enormous amount of time to complete the model. Similarly, a too short time horizon might hinder modelers from observing important dynamics in model behaviors (e.g., acceleration), while a too long one could make the model unnecessarily complicated (J. Sterman, 2000). Hence, in this thesis, based on the formulation and scope of the problem of interest, I only included the most important variables and feedback processes that are important for analyzing the dynamic impact of big data analytics on customer acquisition and firm revenue. A time horizon of 17 years was also selected such that we have enough time to capture all the most significant trends in the behaviors. Further, I used the first 7 years (2013-2019) to fine-tune the model to describe the historical behavior and the last 10 years (2020-2029) to forecast the impact of different investment policies.

4.3 Major Assumptions

4.3.1 Excluding big data velocity and variety

Big data velocity refers to how quickly are data generated, processed and analyzed, while big data variety refers to how diverse are the types of data sources (Ghasemaghaei & Calic, 2019; Lam et al., 2016). While they are two important drivers of the value of big data (e.g., Erevelles et al., 2016), measuring big data velocity and variety has been a known challenge to previous studies (e.g., Lam et al., 2016), leading to the lack of previous studies on the effects of big data velocity and variety on the quality of big data. In addition, real data on how big data velocity and variety have been changing over time at the selected firms in this thesis is not readily available. Collecting extra data (e.g., through a survey or interview) is also not possible as these firms are located in US. Furthermore, to improve big data velocity and variety, firms are mostly required to invest in recruiting more employees (e.g., data scientists, data analysts, etc.), as well as training employees so they can collect, process (e.g., clean and combine, etc.), and analyze big data more efficiently (Davenport, Barth, & Bean, 2012; Leaser, 2014). As this thesis does not focus on employee management and development, I decided to not to include big data velocity and variety in my system dynamics model.

4.3.2 Similar marketing responsiveness between win-back and new customers

Customer reacquisition (also known as win-back) refers to the process of bringing back customers who had decided to terminate their relationship with the firm (Pick, Thomas, Tillmanns, & Krafft, 2016). As firms have increasingly become customer-centric, the concept of customer reacquisition has recently attracted much attention from researchers and practitioners (Kumar, Bhagwat, & Zhang, 2015). Although there are reasons to believe that win-back customers might respond to marketing in a different way than the first-time customers (e.g., Park, Park, & Schweidel, 2018), no empirical evidence has been found in the literature. Hence, in this study, for simplification, it is assumed that customers after churning will simply become potential customers in the next period and be available for firms to re-target and acquire.

4.3.3 The repetition of direct marketing has no impact

Being exposed to a marketing content multiple times means that a customer would become highly familiar with the advertising content and the advertised firm. On the one hand, these customers might learn more about the message and the product, leading to more favorable attitudes (Cacioppo & Petty, 1979). On the other hand, they might feel bored and choose to ignore the advertisement in the future, leading to less favorable attitudes and lower purchase intentions (Pechmann & Stewart, 1988). Existing evidence has demonstrated that the effect of mass advertising repetition might be nonlinear and follow an inverted U-shaped curve (Schmidt & Eisend, 2015). However, previous research has also found that sending direct emails to customers many times would not change their transactional behaviors (van Diepen, Donkers, & Franses, 2009a), although it does lead to irritation. Hence, in this study, I assume that people who have been targeted (e.g., received direct marketing contact from the firm) but decided not to become a customer (i.e., subscriber) will simply become potential customers again in the next period and will be available for firms' further targeting and direct marketing efforts.

4.3.4 Price is exogenous to the model

Following previous research in similar industries (e.g., Rahmandad & Sibdari, 2012), in this analysis, I assume that the price of firms' products (or wireless services) are not determined by the main behavior of the model, namely the number of customers. Indeed, existing evidence suggests that the impact of competition and demand on the price of telecommunication services is rather limited, while the strongest effect comes from cumulative investments of firms in infrastructure and cutting-edge telecommunication technologies such as a new 4G technology in 2010 or 5G in 2019 (Jeanjean, 2015; Nicolle, Grzybowski, & Zulehner, 2018). Hence, it is reasonable to assume that the price used in this thesis is exogeneous to the firms' market size and that they are determined by the development of technology in the whole industry.

4.3.5 Only two firms in the market

The telecom sector in US is an increasingly growing industry with more than 30 wireless service providers listed by the Cellular Telecommunications & Internet Association (CTIA, 2020). Following previous research in market simulation (e.g., Frank M. Bass, Krishnamoorthy, Prasad, & Sethi, 2005), in this thesis, I focus on two telecom firms, T-Mobile and Verizon and assume that this market is a dynamic duopoly with these only two firms competing against each other. The firms are strategically chosen such that while Verizon is dominating the market with a large customer base (i.e., market share of 30%), T-Mobile is a smaller firm with a small customer base (i.e., market share of 15%). In the next chapters, I will explore different scenarios and policies in which Verizon takes advantages of its large customer base (e.g., economies of scale) how T-Mobile can respond to gain benefits from its BDA investments.

4.3.6 Excluding upgrading, downgrading, and cross-buying

In this thesis, for simplicity reason, I assume that there is only one single product served by telecom firms with a single price, namely the wireless communications service. In fact, telecom firms do not only offer mobile phone subscriptions, but they also sell phones and devices, extra mobile data, as well as other services such as home broadband. However, given that subscription fees from mobile phone plans are still the dominant revenue generator in the industry (van de Weyer & Costers, 2020), I only focus on the number of subscribers and the corresponding revenue and profit as the main behavior of my model and collect price information accordingly. Though customers might also move from one mobile phone plan to another one (e.g., upgrading and downgrading), or buy extra services such as mobile data (cross-buying), I also exclude them from my system dynamics model due to time constraint and the lack of necessary data.

4.3.7 No Direct Marketing Targeted at Customers of the Competitors

It is also assumed that direct marketing activities are only used by the firm to target the potential customers and not used as an offensive marketing strategy to attract customers of the competitors. In fact, the effect of competitive direct marketing targeted at the customers of the competitors is complex and not always positive. For example, van Diepen, Donkers, and Franses (2009b) find that sending direct marketing contacts to the competitors' customers makes them aware of their needs for the product category rather than aware of the firm's brand. As such, these competitive marketing activities often increase sales for the whole industry, and in favor of the firms with highest product attractiveness. As there is no clear mechanism underlying this effect, I decide to exclude this from the model.

4.3.8 Limited Knowledge of Customers Before 2013

For simplicity purposes, I assume that both firms have very limited knowledge of customers before the start of my simulation period (i.e., 2013). This assumption implies that firms hadn't implemented any serious BDA investments before. In other words, both firms have a similar starting point in terms of using big data and BDA so it would be easier for us to compare the impact of BDA investments on their performance.

4.3.9 No Simultaneous Targeting

It is also assumed that each potential customer can only be targeted by one firm at a time. This is a necessary assumption to ease the calculation of stock variables related to number of (potential) customers.

4.4 Model Structure

As mentioned above, my system dynamics model is composed of five major modules: Market, Big Data Value, Knowledge Application, Business, and Investment Policy. In this section, I will describe the associated stock and flow diagram of each module in full detail. The full SFD can be found in Appendix 1.

4.4.1 The Market Module

The Market module involves the dynamic interdependence between potential customers, target customers, and total customers (Maier, 1998; Walther, Wansart, Kieckhäfer, Schnieder, & Spengler, 2010) (see Figure 6).

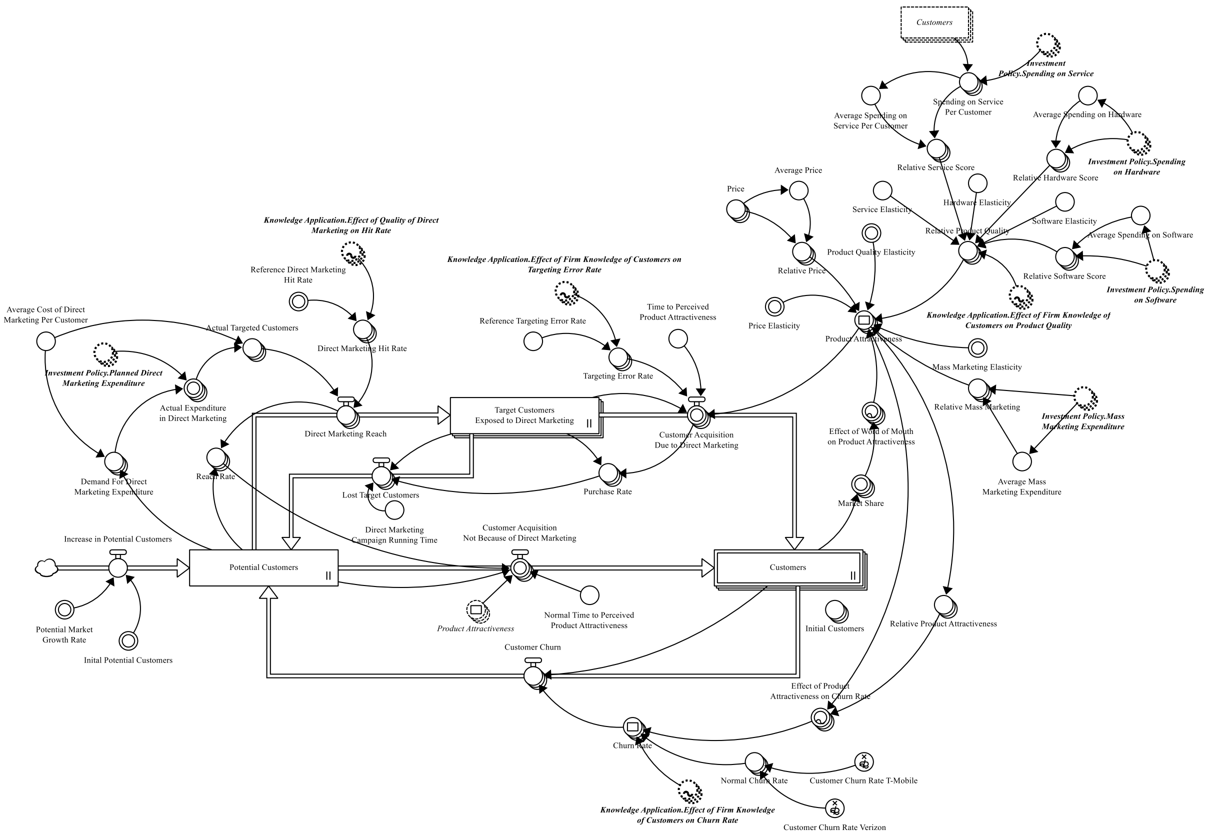


Figure 6. An Overview of the Feedback Structure of the Market Module

This module starts with the targeting process. The stock of Potential Customers reflects the total target market of the firm which contains everyone who buys the category (Romaniuk, 2012). Among these people, not everyone would respond to the firm's direct marketing contacts, and not everyone would be interested in the firm's product. Hence, firms typically decide whether they should target everyone and plan a direct marketing budget accordingly, which is an input from the Policy module. The model therefore compares between the planned direct marketing budget and the expenditure if the firm decides to target everyone (Demand for Direct Marketing Expenditure), and the actual expenditure is the lower value between them. If the firm decides to only target a smaller group of potential customers who are the most responsive to the firm's direct marketing activities, certain targeting rules (e.g., age, gender, income, etc.) would be used. However, a typical targeting policy, which is proposed based on modeling customers' responsiveness toward marketing activities (X. Dong, Manchanda, & Chintagunta, 2009), always involves a certain amount of errors (Fong, Fang, & Luo, 2015). As people who are wrongly targeted will be less responsive toward direct marketing, this targeting error will therefore reduce customer acquisition due to direct marketing (i.e., less customers buy after receiving direct marketing contacts). It is of note that the targeting error will decrease when the firm acquires more knowledge about its customers, which is an input of the Knowledge Application module,

The actual expenditure in direct marketing divided by the average cost of direct marketing per customer results in the total number of prospective customers who are actually targeted. This number, multiplied by the direct marketing hit rate (e.g., the probability that a customer will open and read through a direct email, etc.), then determines how many prospective customers whom the firm has reached through their direct marketing activities (Direct Marketing Reach). It is of note that the direct marketing hit rate is affected by the quality of direct marketing, which is an input of the Knowledge Application module.

Direct Marketing Reach then flows into the stock of total target customers who were exposed to direct marketing, which then determines the number of new customers acquired through direct marketing due to product attractiveness. People who were exposed to direct marketing but choose not to become customers will flow back into the stock of potential customers. Potential customers, in addition to targeted customers who chose not to expose themselves to the direct marketing content (e.g., do not open the email, decline a call from telemarketers, etc.), can still become customers due to other activities of the firm such as mass marketing or word of mouth. As direct marketing is assumed to be the most effective channel in this study, time to perceive product attractiveness when customers are acquired through direct marketing is shorter than when they are acquired through other channels. Note that product attractiveness is determined by relative price, relative quality, relative mass marketing expenditure, and word of mouth. As mentioned in Chapter 2, product quality increases when the firm's knowledge of customers increases, which is an input of the Knowledge Application module. Both of the firm' knowledge of customers and relative product attractiveness then determine how likely is that a customer will leave the firm (Churn Rate). After churning, customers come back to the potential market and are available again for all the firms.

4.4.2 The Business Module

The Business module integrates financial outcomes of the firm including its total revenues and expenses. The total expenses include the firm's investments in BDA activities, direct marketing quality, and product quality (i.e., service, hardware, and software), in addition to the firm's expenditure on big data storage cost, big data collection cost, (direct and mass) marketing costs, and other costs. Note that big data storage cost is determined by big data volume which is an input of the Big Data Value module. Regarding the total revenues, I assume that the firm follows a subscription-based business model such that firm revenue is determined by the recurring payments made by customers in exchange for their subscriptions. New customers, however, must pay a slightly higher amount in the first period due to activation fee (e.g., Statt, 2019). Otherwise, net revenue coming from subscription fee remains the same from the second period onward. The total number of new customers acquired through direct marketing and other reasons is an input of the Market module. Total profit is calculated as total revenues subtracted by total expenses, and is discounted to compute the expected present value (Oliva, Sterman, & Giese, 2003).

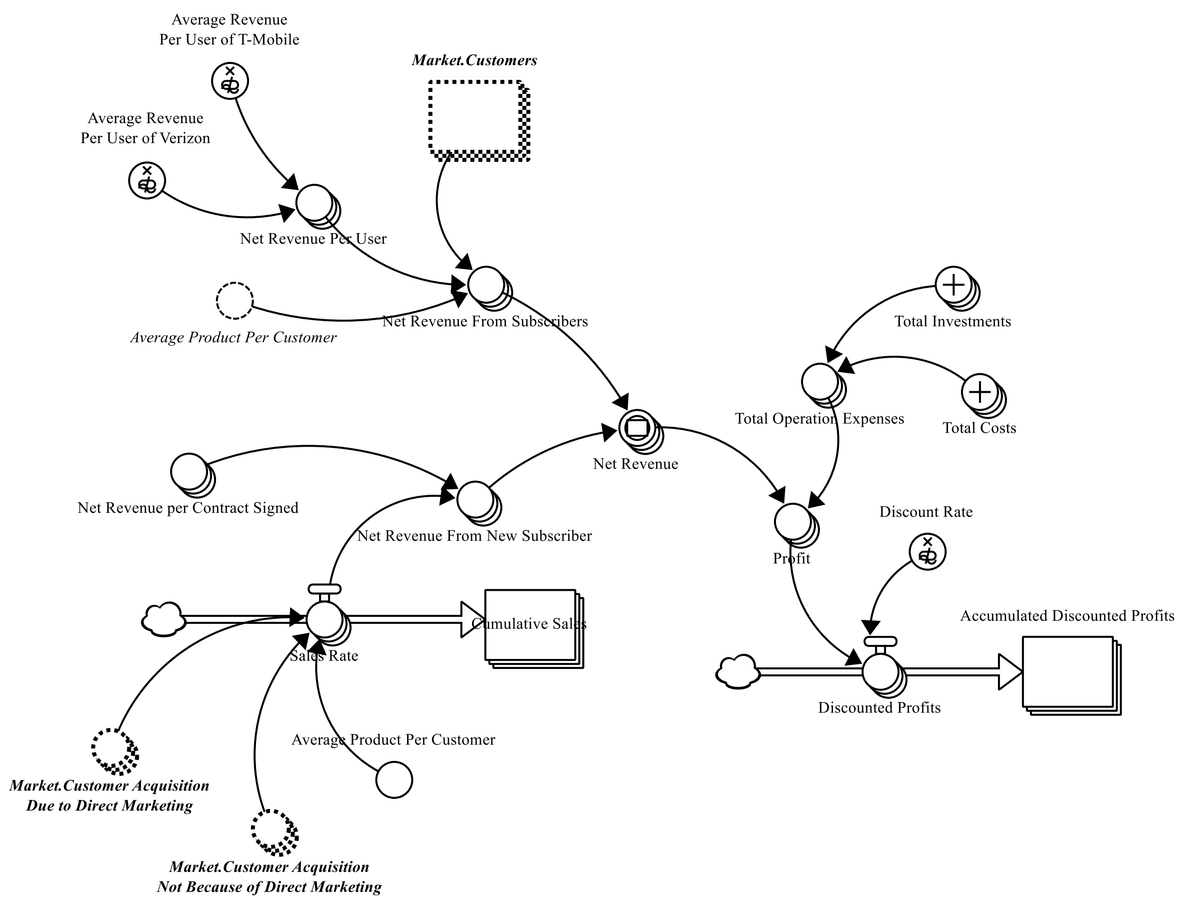


Figure 7. An Overview of the Feedback Structure of the Business Module

4.4.3 The Big Data Value Module

The Big Data Value Module represents the firm's efforts to convert big data into valuable customer insights, a core part in my model structure. As discussed in Chapter 2, the model focuses on two major characteristics of big data: big data volume and big data quality. In this analysis, big data volume increases in two major ways. First, firms get more data when they recruit new customers. These data refer to basic information such as age, gender, address that is normally provided when a new subscription is established. Second, firms can invest in extra data collection activities such as customer surveys, or use third-party services such as Facebook Insights and Google Analytics to enhance its data base (e.g., Goddard, 2018). The desired data that the firm wants to acquire from each customer is calculated as a multiple of the acquired basic data and will be used to compute the desired cost that the firm wants to spend on extra data acquisition. The actual data acquisition expenditure, which is determined as the lower value between the desired and the planned cost of data acquisition, will affect the flow of data acquisition into the stock of Data Volume.

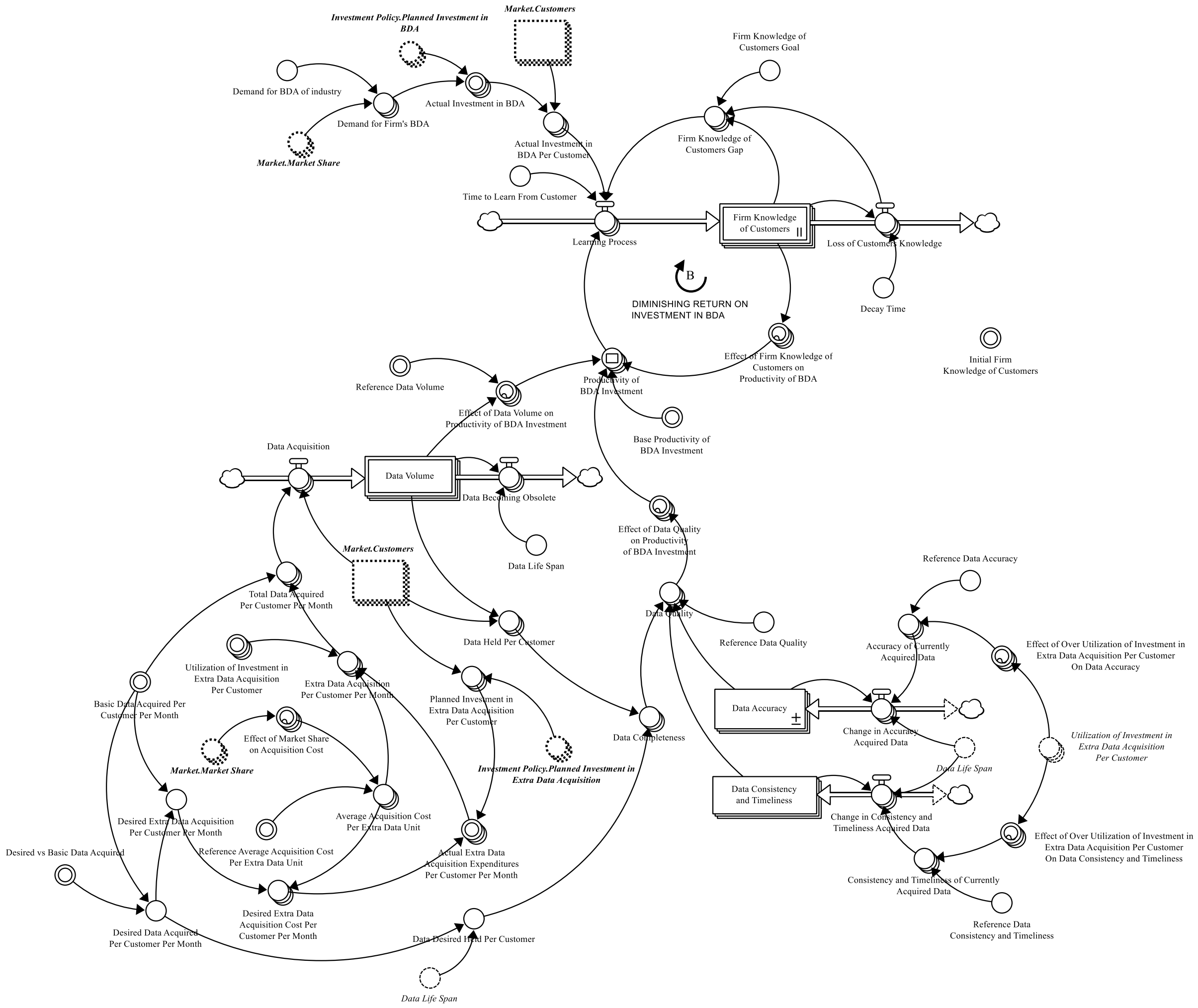


Figure 8. An Overview of the Feedback Structure of the Big Data Value Module

In contrast, data quality is endogenous and subject to the utilization of investments in big data volume. More specifically, the firm might decide to over-utilize its expenses in extra data acquisition to collect more data in order to achieve better data completeness at the cost of lower data accuracy. For example, people often answer surveys in exchange for a certain amount of compensation. If the length of the survey increases (e.g., so that firms can ask more questions to collect more information) without any increase in compensation (i.e., overutilization of the cost), people tend to be more careless in their responses, leading to a lower level of accuracy and consistency (Deutskens, de Ruyter, Wetzels, & Oosterveld, 2004). As such, the higher the utilization rate of investment in extra data acquisition, the higher the data completeness, but the lower the data accuracy will be, followed by the lower consistency and data timeliness. Following previous research in data quality management (e.g., Peltier et al., 2013), the four factors including data completeness, data accuracy, data consistency, and timeliness then determine the quality of the big data. The data is considered more quality, if it is more complete, accurate, consistent, or people can get it in a more timely manner.

The productivity of BDA investments is positively influenced by big data volume and big data quality such that larger and more quality data give the firm better opportunities to employ more advanced and sophisticated analytics methods, leading to more productive BDA activities (Erevelles et al., 2016). The product of actual investment in BDA and the productivity of BDA investments, which is delayed by the time to learn from customers (i.e., delayed effect of learning), results in the learning process which flows into the stock of Firm Knowledge of Customers. The actual investment in BDA depends on the demand from the whole industry as well as the firm policy, which is an input of the Policy module. Note the productivity of BDA investments will decrease when the firm's knowledge of customers increases, resulting in a balancing loop "Diminishing returns of investment in BDA". I will explain this loop in the next part.

4.4.4 The Knowledge Application Module

As shown in the Knowledge Application module, the firm's knowledge of customers (i.e., customer insights from big data) affects customer acquisition in three major ways. First, the firm uses its knowledge to reduce the error rate of the targeting process and to increase the quality of direct marketing activities. On the one hand, better firm knowledge of customers results in better targeting rules, meaning that people targeted are the ones who have the highest probability to respond to the firm's direct marketing. On the other hand, customer knowledge helps the firm become more productive in its investment in direct marketing. For example, the firm might be able to select a better image to include in their direct email personalized for each customer. The increase in the quality of direct marketing is determined by the productivity of direct marketing investment and the actual investment in direct marketing, with a certain delay in the learning process (Time to Increase Quality of Direct Marketing). Note that direct marketing investment depends on the firm policy, which is an input of the Policy module. The increase in the quality of direct marketing will flow into the stock of Quality of Direct Marketing, which in its turn will lower the productivity of direct marketing investment, following the law of diminishing returns of investment. I will explain this balancing loop in the next part.

Second, as mentioned in Chapter 2, the firm also uses its knowledge of customers to increase product quality. Previous research has demonstrated that big data provides important insights for the process of new product development, especially for advancing the product innovation and design, idea creation and testing, technical implementation, commercialization, and pricing (e.g., Antons & Breidbach, 2017; Belyh, 2019). Tidy Dry Cleaners, a dry-cleaning franchise owned by Procter and Gamble, is a typical example of how a new product is developed from customers insights collected from analyzing big data on consumer household cleaning habits (Belyh, 2019).

Finally, churn rate is reduced when the firm's knowledge of customers increases. Existing evidence has shown that loyalty programs can be substantially benefited from the insights derived from large data sets of transactional and demographic information (Lee, Lee, & Sohn, 2013). In particular, BDA activities including machine learning and AI can help firms personalize customer experience and respond more quickly to customers' needs and concerns, reducing disruption to their use of service, leading to a higher rate of customer retention (Aradhya, 2020).

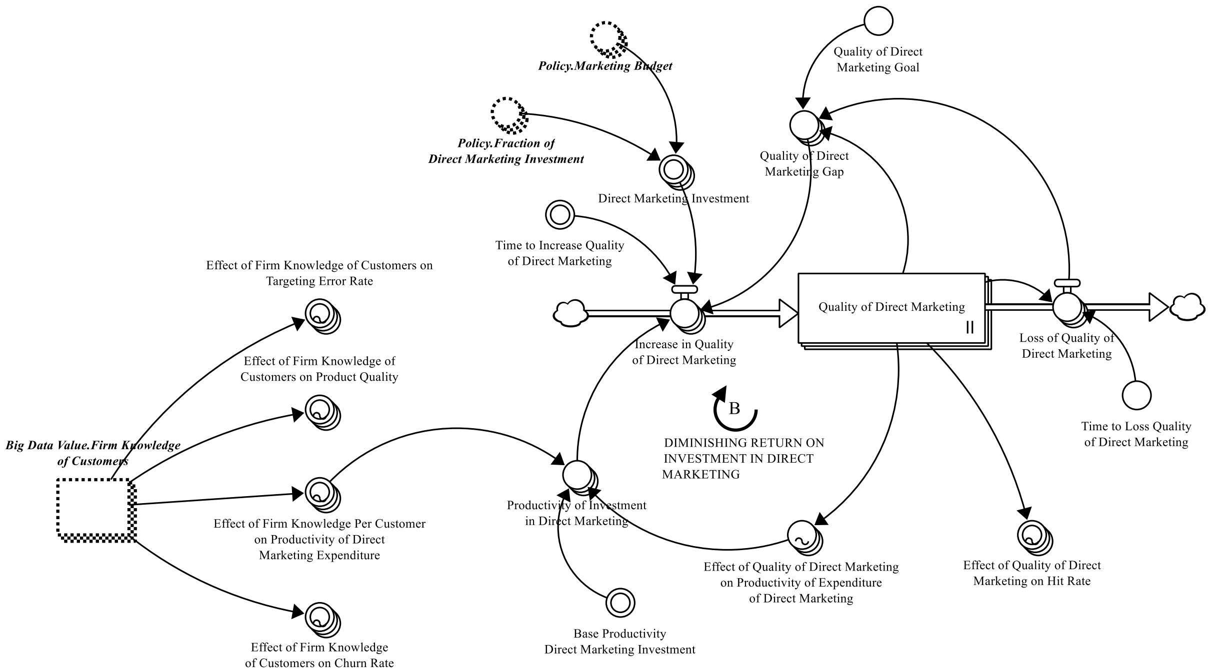


Figure 9. An Overview of the Feedback Structure of the Knowledge Application Module

4.4.5 The Investment Policy Module

This Investment Policy module contains parameters that reflect the decisions of firms regarding the amount of money invested in BDA, extra data acquisition, and other activities to improve product quality such as service, hardware and software. For the sake of simplicity, it is assumed that the planned investments are fractions of the firm revenue, which is an element of the Business module (Davidsen et al., 1990). In addition, this module includes the planned budget for marketing activities, namely expenditures of both direct marketing and mass marketing activities. These fractions are computed based on the actual ratios of investments to firm revenue across years, as reported in the firms' annual financial statements (T-Mobile, 2007-

2019; Verizon, 2006-2019). In Chapter 7 and 8, I will explore this module further to discuss different market scenarios and propose different investment policies for firms to help them exploit the benefits of big data.

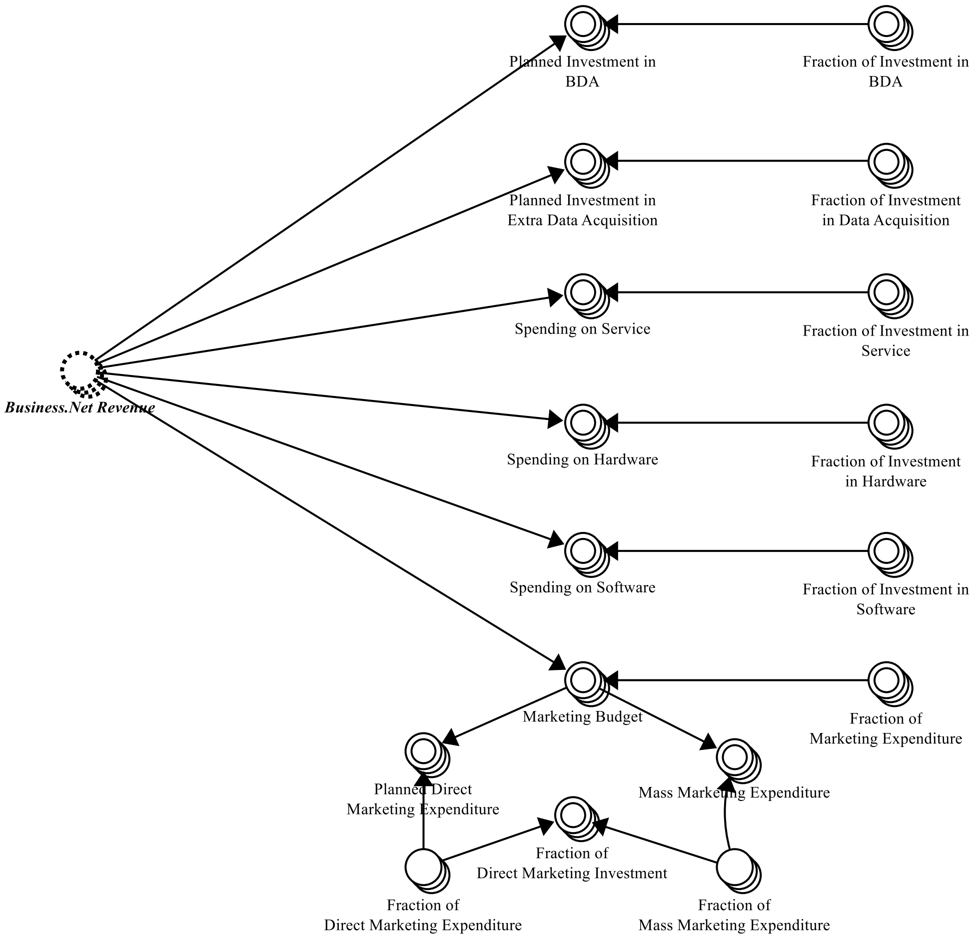


Figure 10. An Overview of the Feedback Structure of the Investment Policy Module

4.5 Feedback Analysis

According to John D. Sterman (2001), all dynamics in the behavior of interest can be understood through examining the interaction of different feedback processes in the model. In fact, there exists two types of feedback loop: reinforcing (or positive) and balancing (or negative) loops. While reinforcing loops explain how a system grows or develops through self-reinforcing or self-amplifying, balancing loops describe a process that a system tries to move itself to a desired state (the equilibrium) (John D. Sterman, 2001). In this part, I will elaborate the overall CLD (see Figure 11), which represents the simplified version of my model (see Appendix 1 for the full SFD), with the five major loops driving and capturing all the dynamics of the main model behavior.

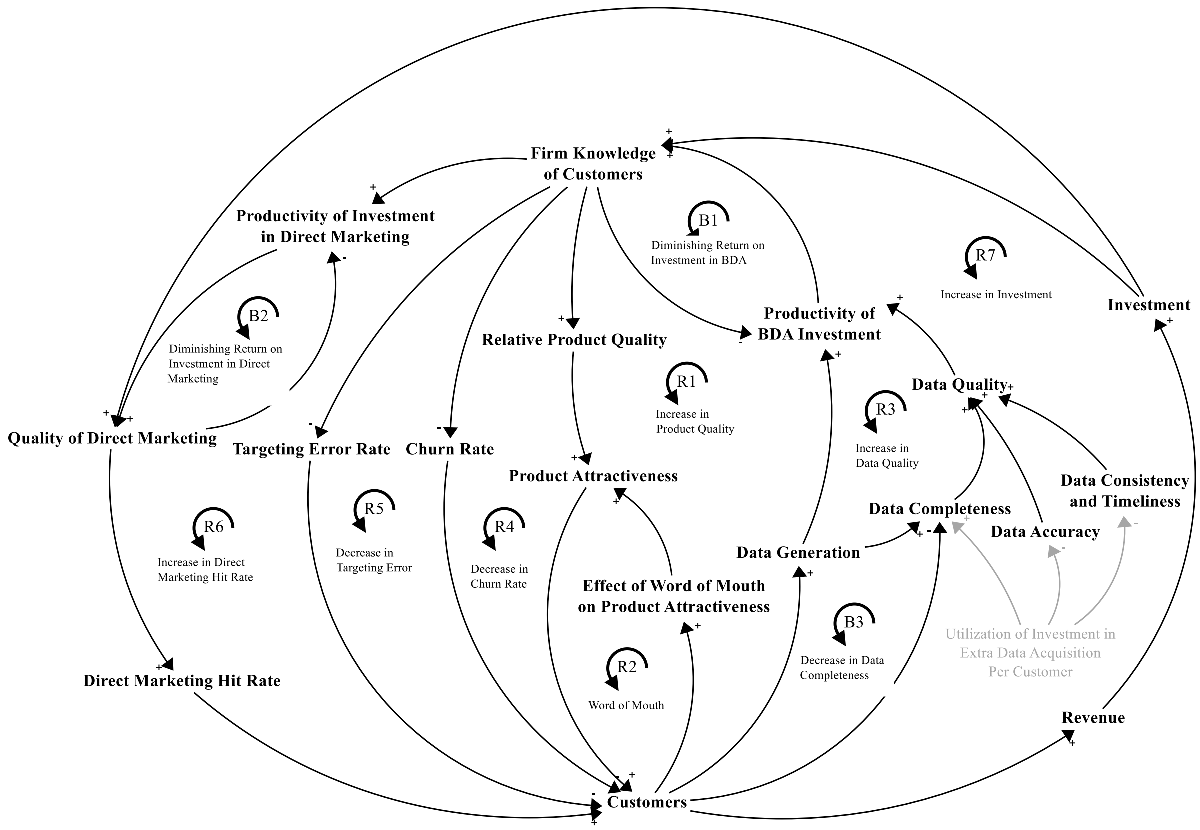


Figure 11. An Overview of the Causal Loop Diagram (CLD) of the Model

4.5.1 Reinforcing Loops

a) Increase in Product Quality – Loop R1

The reinforcing loop *Increase in Product Quality* (R1) describes the ability of the firm to grow its customer base by making its product/service relatively more attractive than its competitors. More particularly, when the firm's product quality increases relatively to the average product quality in the market, its product attractiveness increases, allowing the firm to acquire more customers and leading to a higher number of total subscribers. Consequently, the higher the number of customers, the more data the firm has, leading to higher productivity of the BDA investment. Enhanced productivity of investment in BDA will lead to more firms' knowledge of customers. The more the firm's knowledge of customers, the better it can do to improve its product quality again. This feedback process is a reinforcing loop as an initial increase in product quality, after pushing all other loop elements up, would lead to a further increase in the total number of customers and subsequently result in another increase in product quality.

b) Word of Mouth – Loop R2

The reinforcing loop *Word of Mouth* (R2) shows how the firm can increase its number of customers without investing in any traditional marketing communication tools but rather relying on the word-of-mouth effect. Word of mouth has been studied extensively in the marketing literature and is known to be a strong determinant of customer adoption of new products (Trusov, Bucklin, & Pauwels, 2009) and customer retention (Godes & Mayzlin, 2004). Particularly, word of mouth is considered more credible than other marketing tactics as people tend to trust words from other customers more than those from the firm itself (Kozinets, Valck, Wojnicki, & Wilner, 2010). According to the previous literature on diffusion (Frank M. Bass, 1969; Rogers, 1995), when the number of subscribers increases, potential customers have more chance to access information about the firm's products and services from actual customers, leading to a higher level of awareness and subsequently purchase intentions (Paich & Sterman, 1993). Furthermore, previous research in social norms has demonstrated that customer experience with the firm's product tends to be biased by those shared from other customers (Boothby, Clark, & Bargh, 2014; Cialdini, 2007), explaining why word of mouth exerts a strong positive impact on customers' product evaluation (Duan, Gu, & Whinston, 2008). Hence, I suggest that an initial increase in the number of customers would lead to stronger word of mouth, making the firm's product relatively more attractive than other alternatives in the market which in turn leads to further increase in the number of customers. That summarizes my reinforcing loop *Word of Mouth* (R2).

c) Increase in Data Quality – Loop R3

The reinforcing loop *Increase in Data Quality* (R3) illustrates the ability of the firm to grow its customer base through big data. Specifically, firms gain more data when the number of total customers increases, making its database becomes more complete. As data completeness is an important determinant of big data quality, the quality of the database increases consequently. While poor quality data can hinder the data analysis process and ultimately hurt the results of analytics activities (Ramasamy, 2019), high quality data instead fosters the data processing and analytics process, leading to higher productivity of BDA investments. When BDA investments are more productive, firms gain more customer insights and become more knowledgeable about their customers. As in the reinforcing loop R1, the firm's increased knowledge of customers will lead to increase in the product's relative quality and perceived attractiveness. This will consequently lead to more customers being recruited. To sum up, an initial increase in the number of customers leads to enhancement in the data quality and subsequently results in further increase in the number of customers, making it another reinforcing loop.

d) Decrease in Churn Rate – Loop R4

The reinforcing loop *Decrease in Churn Rate* (R4) describes the impact of big data on the firm's customer acquisition through reducing customer defection. More specifically, when the number of total customers increases, the focal firm acquires more data, leading to enhanced productivity of BDA investments and subsequently more knowledge of customers. With more customer insights into the customers' product experience and problems, the firm will be able to not only respond to their complaints more quickly, but also nurture customer loyalty through unique loyalty programs or personalized promotions. In other words, this leads to lower customers' churn rate, which in turn will have a positive impact on the number of total customers.

e) Decrease in Targeting Error – Loop R5

The reinforcing loop *Decrease in Targeting Error* (R5) explains how big data exerts a positive impact on customer acquisition through its use in the targeting process. Indeed, like the reinforcing loop R4, when the number of total customers increases, the volume of the acquired data is larger, productivity of BDA investment increases, and the firm acquires more knowledge of their customers. These customer insights into customer behaviors could help the firm identify which characteristics of prospective customers would make them become more valuable customers in the future. For example, based on customer insights, the firm might conclude that its most valuable customers are females in their 30s and use these criteria to define its target market. The more knowledge the firm has, the less error the firm makes in the targeting process. Additionally, the less targeting the firm has, the more customers it can acquire. As an initial increase in the number of customers leads to further increase in the firm's customer base through minimizing the targeting error, this process can be referred to as the fifth reinforcing loop in my model.

f) Increase in Direct Marketing Hit Rate – Loop R6

The reinforcing loop *Increase in Direct Marketing Hit Rate* (R6) illustrates the ability of the firm to grow its customer base by improving the quality of its direct marketing activities. Like reinforcing loops R1, R4, and R5, when the total number of customers increases, the firm gets more knowledge of customers due to bigger data volume. The increased knowledge of customers helps the firm improve the quality of their direct marketing activities and therefore increase hit rate, which is the probability that customers will expose themselves to the marketing messages (e.g., opening the firm's direct emails or reading its brochures). When direct marketing hit rates increases, there are more chances that customers would respond to the marketing requests and become subscribers. Thus, the total of customers will consequentially increase further, making it the sixth reinforcing loop in the model.

g) Increase in Investment – Loop R7

The reinforcing loop *Increase in Investment* (R7) describes how the firm can acquire more customers by increasing its investments in BDA and direct marketing. As mentioned above, firms can invest money in BDA to increase its knowledge of customers, which subsequently leads to higher quality of direct marketing, lower churn rate, lower targeting error, and higher product quality. Similarly, firms can also invest in direct marketing to enhance its quality directly. Consequently, as shown in reinforcing loops R1, R4, R5, and R6, these investments would lead to higher number of customers. For simplicity purposes, these investments are assumed to be fixed fractions of firm revenue (Davidsen et al., 1990), which is approximately the product of the number of total (new and existing) customers and the subscription fee. Given that the development in the number of customers causes corresponding increase in revenues and investments which again produces positive feedback on the number of customers, I conclude that this is a reinforcing loop.

4.5.2 Balancing Loops

a) Diminishing Return on Investment in BDA – Loop B1

The balancing loop *Diminishing Return on Investment in BDA* (B1) describes the limitation of the benefits from the firm's investment in BDA activities. An increase in the productivity of the firm's investment in BDA allows the firm to get more customer insights per each dollar invested. In other words, the higher productivity of investment in BDA leads to more knowledge of customers that the firm can get. Nevertheless, the more knowledge the firm has per each customer, the less undiscovered insights into the customer's behavior the firm can find, making it harder gain extra knowledge with future investments. In other words, when the firm's knowledge of customers increases, the productivity of investment declines. Hence, when the firm's knowledge of customers is reasonably high, this feedback process, therefore, limits its expansion to its maximum, resulting in the first balancing loop in my model.

b) Diminishing Return on Investment in Direct Marketing – Loop B2

The balancing loop *Diminishing Return on Investment in Direct Marketing* (B2) explains the limitation of the benefits from the firm's investment in direct marketing activities. Like the balancing loop B1, a higher productivity of the firm's investment in direct marketing means that for each dollar invested, the quality of the firm's direct marketing increases at a higher speed. However, the better the quality of the firm's direct marketing, the less things the firm can do to improve it. In other words, at this point, an increase in the direct marketing quality would decrease the productivity of the firm's investment. In conclusion, when the quality of the firm's direct marketing becomes higher, this feedback process will hinder its expansion so it will not exceed its maximum. This leads to my second balancing loop in the model.

c) Decrease in Data Completeness– Loop B3

The balancing loop *Decrease in Data Completeness* (B3) explains the limited growth of big data quality. More specifically, when the firm acquires more new customers, the average acquired information per customer decreases, leading to lower data completeness. Lower data completeness leads to lower quality of big data, which reduces the productivity of the firm's investment in BDA. Consequently, the firm's knowledge of customers decreases, leading to lower number of new customers acquired as in the reinforcing loops R1, R4, R5, and R6. In conclusion, when the number of total customers increases, data completeness will hinder its expansion through a feedback process, resulting in another balancing loop B3 in the model.

4.6 The Dynamic Hypothesis

Based on the above theoretical reasoning, my main dynamic hypothesis is that the proposed model will capture the dynamic behaviors of interest including the firms' customer acquisition and financial performance (see Reference Behavior in part 1.3 of Chapter 1). When no policies are implemented, the model predicts that, since 2020, T-Mobile will experience an increasing growth rate of the customer base, leading to a steady increase of net profit and a higher market share. In contrast, since 2020, Verizon will experience a decreasing growth rate of the total number of customers, explaining a decline in its market share, even though its net profit is still increasing slowly.

One important factor that determines of the dynamics in the developments of firms' market share is the firm's knowledge of customers. Indeed, with more knowledge of customers, the firm does not only attract more prospective customers to become its subscribers (as explained by reinforcing loops R1, R5, R6), but also effectively reduce the churn rate (as explained by the reinforcing loop R4), leading to increase in the total number of customers. In addition, the firm's market share can also grow by itself due to the effect of word of mouth (see reinforcing loop R2). The importance of the firm's knowledge justifies the crucial role of investments in BDA, big data acquisition, as well as the trade-off between big data volume and quality (as explained by reinforcing loops R3 and R7). Thus, my another hypothesis is that my proposed policies which are related to the changes in investments in BDA and big data acquisition, and the changes in the trade-off between data volume and quality would lead to improvement in the market share and/or financial performance (e.g., net profit) of the focal firm. It is of note that the returns on investments in BDA and marketing are diminishing when the benefits increase (as explained by the balancing loops B1 and B2). In addition, the growth of the customer base is also limited by the decrease in data completeness (as explained by the balancing loop B3). In Chapter 5, I will test whether this model structure could closely capture the observed behaviors. Further tests of this dynamic hypothesis will be reported in Chapters 6 (model validation), 7 (scenario analysis), and 8 (policy analysis).

Chapter 5: Behavior Analysis

5.1 Model Calibration

Model calibration is the process of investigating the model parameters to obtain the best model structure that results in congruence between the observed and the simulated behaviors (Oliva, 2003). Model calibration is therefore an important part of the system dynamics modeling process such that it helps ensure that the model structure established in this study is a valid representation of the observed behavior in reality, and thus, can be used to performance further test on the suggested investment policies (Khan, Qureshi, & Davidsen, 2020; Oliva, 2003). As explained in the Data Collection part (section 3.2, Chapter 3), although I was trying to collect as much case-specific information about the chosen firms and industry as possible, using a variety of information sources such as firms' annual report and previous literature, it is impossible to gather information for all parameters used in the model. Due to time and resource constraints, I follow previous research (e.g., Khan et al., 2020) to fill in the missing information using educated guess that is informed by logical reasoning and intuition. The values of the calibrated parameters are shown in the Appendix 2.

5.2 Analysis of Baseline Simulation Result

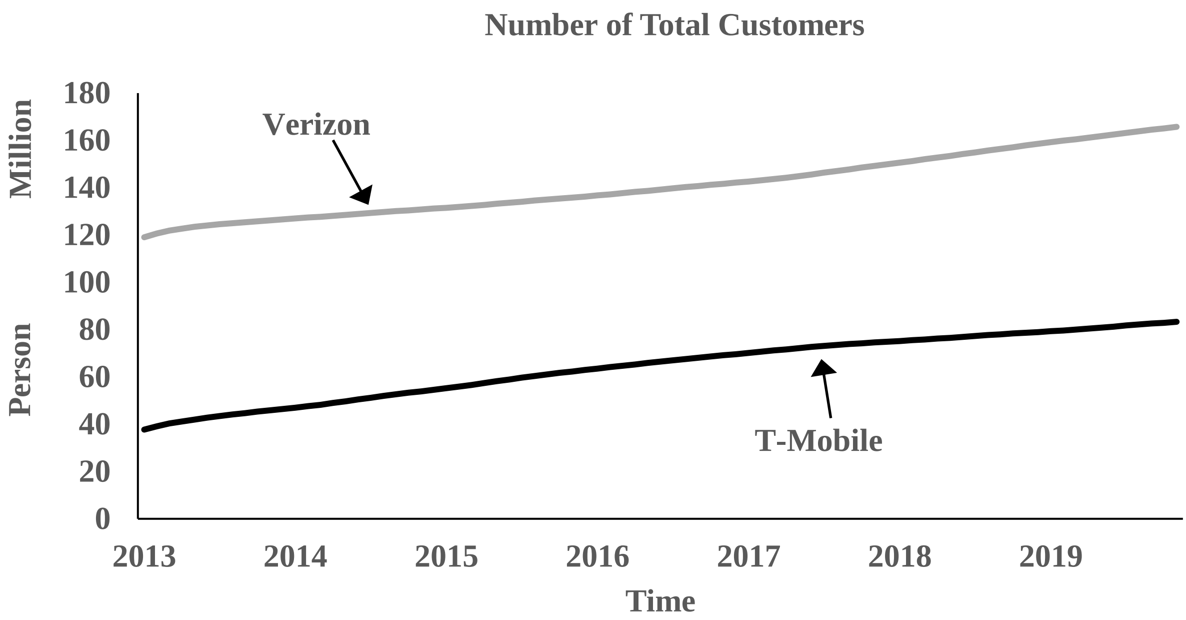


Figure 12. Simulated Number of Total Customers of T-Mobile and Verizon

Figure 12 shows the number of customers of both T-Mobile and Verizon simulated by my model for the study period from 2013 to 2019. As shown in Figure 12, the number of total customers has been steadily increasing since 2013 for both firms. The growth rate of Verizon, nevertheless, is much lower than that of T-Mobile. Indeed, Verizon had roughly a total of 117 million of customers in 2013 which grew into 166 million of customers at the end of 2019 (a percent change of 41.9%, which is equivalent to an average annual growth rate of 0.06%). Similarly, T-Mobile had about 34 million of customers in 2013 which grew into 83 million of customers at the end of 2019 (a percent change of 144.1%, which is equivalent to an average annual growth rate of 0.21%).

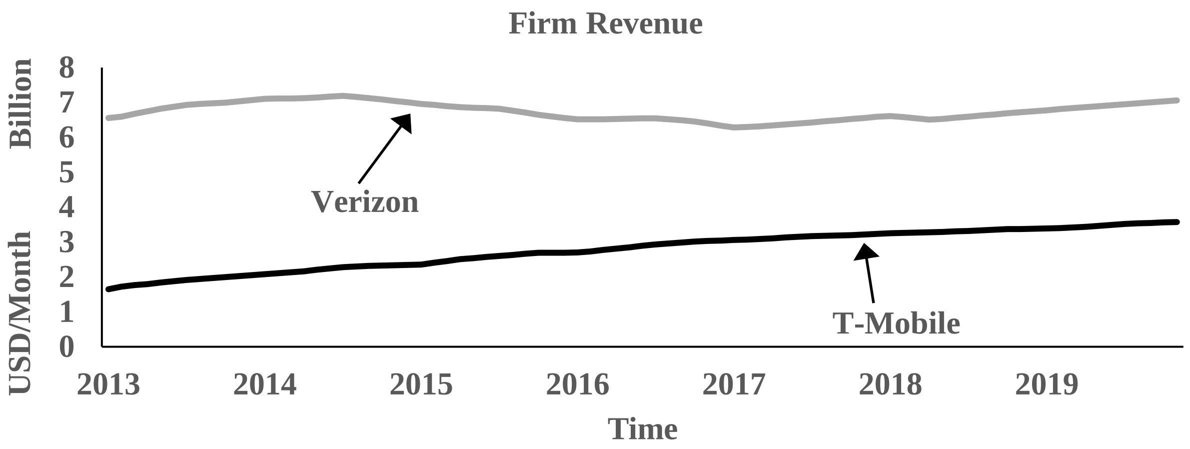


Figure 13. Simulated Firm Revenue of T-Mobile and Verizon

The total revenue per month of T-Mobile, as shown in Figure 13, also increased steadily from 2013 to 2019. Particularly, T-Mobile's monthly revenue has increased from \$1.6 billion in 2013 to \$3.6 billion at the end of 2019, which is equivalent to a percent increase of 129.2% or an average monthly growth rate of 1.5%. Verizon's monthly revenue, instead, has fluctuated between 2013 and 2019 such that it slightly increased until the mid of 2014 and then decreased until 2017 and then increased again until the end of the observation period (2019). Verizon had about \$6.8 billion in 2013 which grew into \$7.1 billion at the end of 2019 (a percent increase of 4.5% which is equivalent to an average monthly growth rate of 0.05%).

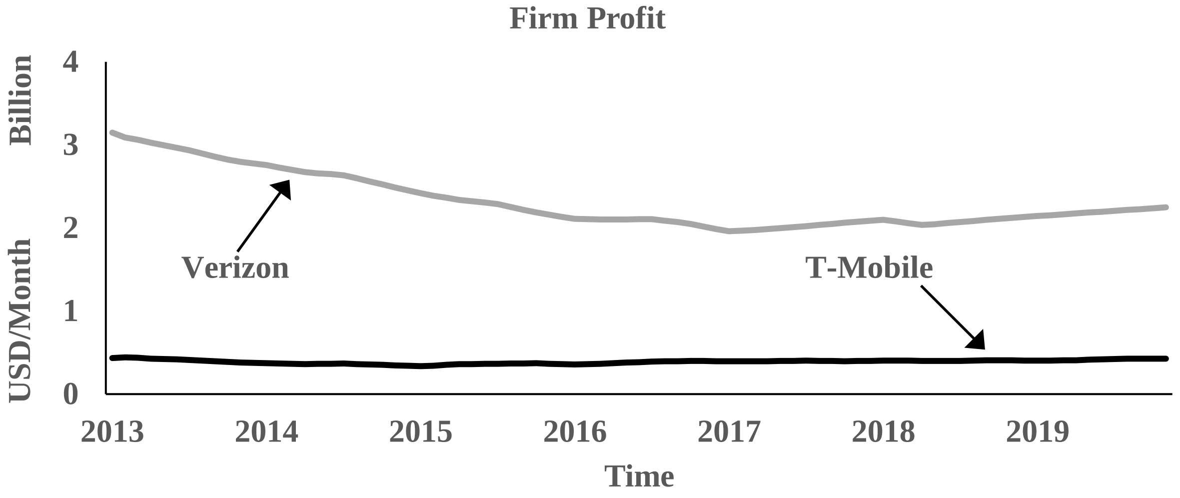


Figure 14. Simulated Firm Profit of T-Mobile and Verizon

In contrast, the total profit per month of T-Mobile, as shown in Figure 14, has stayed stably between 2013 and 2019 while Verizon's profit has decreased between 2013 and 2017 and then slightly increased between 2017 and 2019. Particularly, T-Mobile's monthly profit has slightly increased from \$0.41 billion in 2013 to \$0.43 billion at the end of 2019, which is equivalent to a percent increase of 3.6% or an average monthly growth rate of 0.04%. In contrast, Verizon's monthly profit has declined from \$3.32 billion in 2013 to \$2.25 billion at the end of 2019 (a percent decrease of 32.3% which is equivalent to an average monthly growth rate of -0.39%).

Chapter 6: Model Validation

6.1 Model Validation Overview

Model validation is an important part in the modeling process as it does not only help SD modelers identify potential problems when constructing the model but also provide evaluators with evidence so they can be confident that the model has been properly developed (Forrester & Senge, 1980). As there are so many tests available, in this thesis, I follow Barlas (1996) to perform a set of tests that has been used widely in previous research to formally assess model validity. More specifically, my model validation process is composed of two major steps, including structure and behavior validity, that I will explain in the next parts.

6.2 Structure Validity

These tests are performed to establish confidence in the validity of the structure of the model (Barlas, 1996). It contains two major sets of tests: direct structure tests and structure-oriented behavior tests.

6.2.1 Direct Structure Tests

In these tests, I will directly compare each of the relationships between the model elements with available knowledge about the system structure in reality (Barlas, 1996). Four tests are performed: structure-confirmation test, parameter-confirmation test, direct extreme-conditions test, and dimensional consistency test.

a) *Structure-confirmation test*

Following Forrester and Senge (1980), here I validate the form of the model equations using the existing relationships in the real system, which is particularly based on generalized knowledge in the literature (Barlas, 1996).

Table 2 summarizes the results of my structure-confirmation test. As the main structure of the model follows the existing knowledge from previous literature, it is concluded that the model has established a valid structure and variable relationships.

b) *Parameter-confirmation test*

The parameter-confirmation test aims to assess the consistency between the constant parameters and knowledge of the real system (Barlas, 1996). In fact, the values of all constant parameters in my model are mostly based on case-specific information available on the firm's website, annual reports, and other online sources. See Appendix for more details about the parameters of my model.

Model Structure	**Description**	**Supporting Literature**	**Note**
Market	See 4.4.1, Chapter 4	Previous literature on segmentation and targeting (see 2.3, Chapter 2), customer acquisition, customer retention, and customer relationship management (e.g., Becker, Greve, & Albers, 2009)	For simplicity, the model excludes several variables that might be of interest for future research: customer satisfaction, customer loyalty, etc.
Business	See 4.4.2, Chapter 4	Common knowledge and insights from the firms' financial statements	For simplicity, only the most important and relevant revenues and costs are included.
Big Data Value	See 4.4.3, Chapter 4	Previous literature on big data and the characteristics of big data (see 2.1, Chapter 2)	Excluding big data velocity and variety (see discussion in 4.3.1, Chapter 4)
Knowledge Application	See 4.4.4, Chapter 4	Previous literature on the impact of big data and BDA (see 2.3, Chapter 2)	The model only includes the impact of BDA on marketing, product development, and customer retention. Future research might explore other benefits such as automated customer services, etc.
Investment Policy	See 4.4.5, Chapter 4	Common knowledge and insights from the firms' annual reports	Investment amounts are assumed to be a fixed fraction of the total revenue

Table 2. Structure-Confirmation Test

c) *Direct extreme-conditions test*

In this test, I evaluate the validity of all equations in the model under extreme conditions (Barlas, 1996). For example, one can mathematically derive the outputs of each equation based on the maximum or minimum values of the input variables. Results, as shown in Table 3 below, confirm that the model structure is robust against the anticipated conditions that would occur in reality (Forrester & Senge, 1980).

Variable Name	Equation	Upper Extreme Condition	Response to Upper Extreme Condition	Lower Extreme Condition	Response to Lower Extreme Condition
Actual Investment in BDA	MIN(Policy.Planned_Investment_in_BDA, Demand_for_Firm's_BDA)	"Policy.Planned_Investment_in_BDA" = 10^9 "Demand_for_Firm's_BDA" = 1	Expected: 1 Actual: 1	"Policy.Planned_Investment_in_BDA" = 1 "Demand_for_Firm's_BDA" = 10^9	Expected: 1 Actual: 1
Actual Expenditure in Direct Marketing	MIN(Policy.Planned_Direct_Marketing_Expenditure, Demand_For_Direct_Marketing_Expenditure)	"Policy.Planned_Direct_Marketing_Expenditure" = 10^9 "Demand_For_Direct_Marketing_Expenditure" = 1	Expected: 1 Actual: 1	"Policy.Planned_Direct_Marketing_Expenditure" = 1 "Demand_For_Direct_Marketing_Expenditure" = 10^9	Expected: 1 Actual: 1
Actual Extra Data Acquisition Expenditures Per Customer Per Month	MIN (Planned_Investment_in_Extra_Data_Acquisition_Per_Customer, Desired_Extra_Data_Acquisition_Cost_Per_Customer_Per_Month)	"Planned_Investment_in_Extra_Data_Acquisition_Per_Customer"= 100 "Desired_Extra_Data_Acquisition_Cost_Per_Customer_Per_Month" = 1	Expected: 1 Actual: 1	"Planned_Investment_in_Extra_Data_Acquisition_Per_Customer"= 1 "Desired_Extra_Data_Acquisition_Cost_Per_Customer_Per_Month" = 100	Expected: 1 Actual: 1
Relative Product Quality	(Relative_Service_Score^Service_Elasticity)* (Relative_Hardware_Score^Hardware_Elasticity)* (Relative_Software_Score^Software_Elasticity)*Knowledge_Application.Effect_of_Firm_Knowledge_of_Customers_on_Product_Quality	"Service_Elasticity" = 1 "Hardware_Elasticity" = 1 "Software_Elasticity" = 1 "Relative_Service_Score" = 5 "Relative_Hardware_Score" = 5 "Relative_Software_Score" = 5 "Knowledge_Application.Effect_of_Firm_Knowledge_of_Customers_on_Product_Quality" = 1.3	Expected: 162.5 Actual: 162.5	"Service_Elasticity" = 0 "Hardware_Elasticity" = 0 "Software_Elasticity" = 0 "Relative_Service_Score" = 0.1 "Relative_Hardware_Score" = 0.1 "Relative_Software_Score" = 0.1 "Knowledge_Application.Effect_of_Firm_Knowledge_of_Customers_on_Product_Quality" = 1	Expected: 1 Actual: 1
Product Attractiveness	(Relative_Product_Quality^Product_Quality_Elasticity)* (Relative_Price^Price_Elasticity)* (Relative_Mass_Marketing^Mass_Marketing_Elasticity)*Effect_of_Word_of_Mouth_on_Product_Attractiveness	"Product_Quality_Elasticity" = 1 "Price_Elasticity" = -1 "Mass_Marketing_Elasticity" = 1 "Relative_Product_Quality" = 5 "Relative_Price" = 0.2 "Relative_Mass_Marketing" = 5 "Effect_of_Word_of_Mouth_on_Product_Attractiveness" = 1.3	Expected: 162.5 Actual: 162.5	"Product_Quality_Elasticity" = 0 "Price_Elasticity" = 0 "Mass_Marketing_Elasticity" = 0 "Relative_Product_Quality" = 0.1 "Relative_Price" = 1 "Relative_Mass_Marketing" = 0.1 "Effect_of_Word_of_Mouth_on_Product_Attractiveness" = 1	Expected: 1 Actual: 1

Customer Acquisition Not Because of Direct Marketing	Potential_Customers* (1-Reach_Rate) *Product_Attractiveness/Normal_Time_to_Perceived_Product_Attractiveness	“Potential_Customers” = 10000000 “Reach_Rate” = 0 “Product_Attractiveness” = 1 “Normal_Time_to_Perceived_Product_Attractiveness” = 1	Expected: 10000000 Actual: 10000000	“Potential_Customers” = 10000000 “Reach_Rate” = 1 “Product_Attractiveness” = 1 “Normal_Time_to_Perceived_Product_Attractiveness” = 1	Expected: 0 Actual: 0
Customer Acquisition Due to Direct Marketing	(Target_Customers_Exposed_to_Direct_Marketing* (1-Targeting_Error_Rate) + Target_Customers_Exposed_to_Direct_Marketing*Targeting_Error_Rate* Product_Attractiveness)/ Time_to_Perceived_Product_Attractiveness	“Target_Customers_Exposed_to_Direct_Marketing” = 10000000 “Targeting_Error_Rate” = 1 “Product_Attractiveness” = 1 “Time_to_Perceived_Product_Attractiveness” = 1	Expected: 10000000 Actual: 10000000	“Target_Customers_Exposed_to_Direct_Marketing” = 0 “Targeting_Error_Rate” = 0 “Product_Attractiveness” = 1 “Time_to_Perceived_Product_Attractiveness” = 1	Expected: 0 Actual: 0
Lost Target Customers	Target_Customers_Exposed_to_Direct_Marketing*(1-Purchase_Rate)/Advertising_Running_Time	“Target_Customers_Exposed_to_Direct_Marketing” = 10000000 “Purchase_Rate”= 0 “Advertising_Running_Time” = 1	Expected: 10000000 Actual: 10000000	“Target_Customers_Exposed_to_Direct_Marketing” = 10000000 “Purchase_Rate”= 1 “Advertising_Running_Time” = 1	Expected: 0 Actual: 0

Table 3. Direct Extreme-Condition Test

d) *Dimensional consistency test*

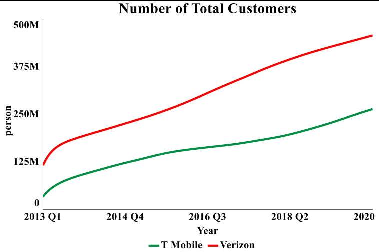
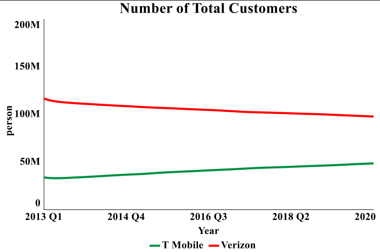
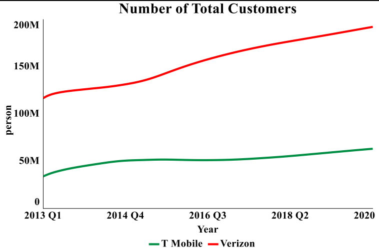
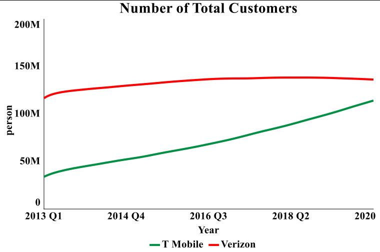
The purpose of this test is to confirm that the model contains valid unit for each variable. Furthermore, the test is used to check whether the units are the same between the left- and the right-hand sides of every equation (Barlas, 1996). As the SD modeling software handles this issue automatically, this test is confirmed as no errors were reported.

6.2.2 Structure-Oriented Behavior Tests

The structure-oriented behavior tests aim to provide simulation results as indirect confirmation of the validity of the model structure (Barlas, 1996). They involve extreme-condition and behavior sensitivity tests.

a) Extreme-condition test

Extreme-condition test aims to evaluate the model behaviors simulated based on extreme values of a certain set of parameters to see whether the simulated behavior would deviate from the anticipated behaviors in the extreme conditions (Barlas, 1996). As shown in Table 4, the results show that all the simulated behaviors reasonably follow our expectations.

Variable	**Upper Extreme Condition**			**Lower Extreme Condition**		
	Upper Extreme Condition	**Anticipated System Behavior in Response to Upper Extreme Condition**	**Simulated System Behavior in Response to Upper Extreme Condition**	**Lower Extreme Condition**	**Anticipated System Behavior in Response to Lower Extreme Condition**	**Simulated System Behavior in Response to Lower Extreme Condition**
Initial Potential Customers	10^9	When the potential market size increases, the total number of customers increases for both firms. The difference between the two firms, however, is expected to remain.		0	When the potential market size is zero, as the total number of customers from both firms remains over years, it is expected that the increase in the number of customers of one firm is equal to the decrease in the number of customers of another firm.	
Base Productivity of BDA Investment	1	When the base productivity of BDA investment is maximal, it is expected that the larger firm with larger customer database will get more benefits and gain more customers, compared to the smaller firm.		0	When the base productivity of BDA investment is minimal, it is expected that BDA activities will give no competitive advantage to the larger firm. Thus, the market will develop in favor of T-Mobile who has a higher product attractiveness	

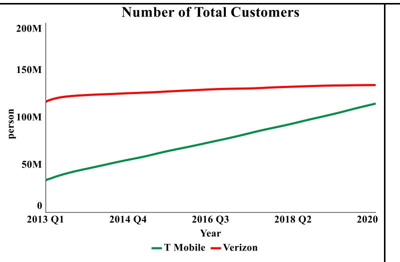
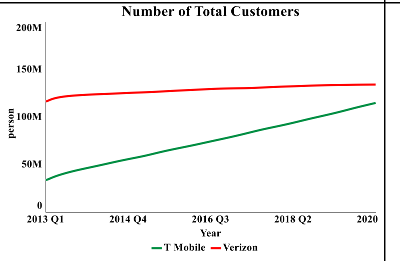
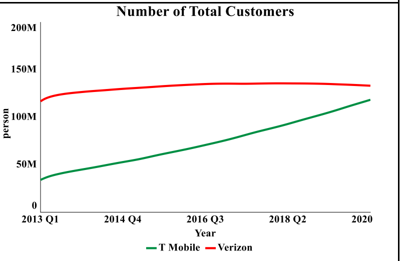
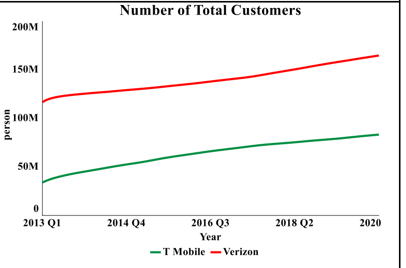
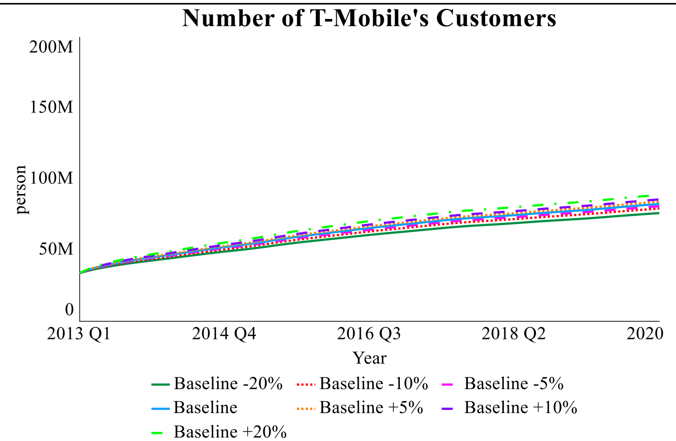
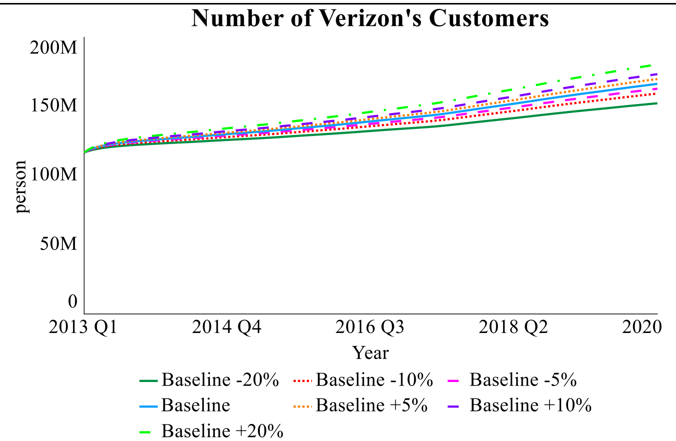
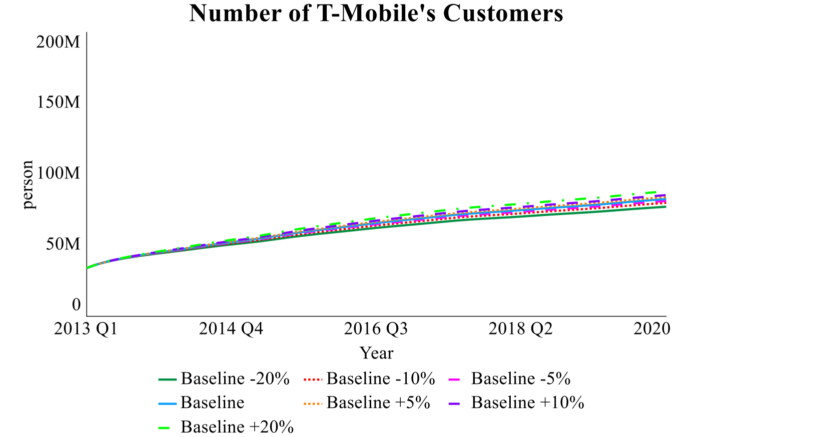
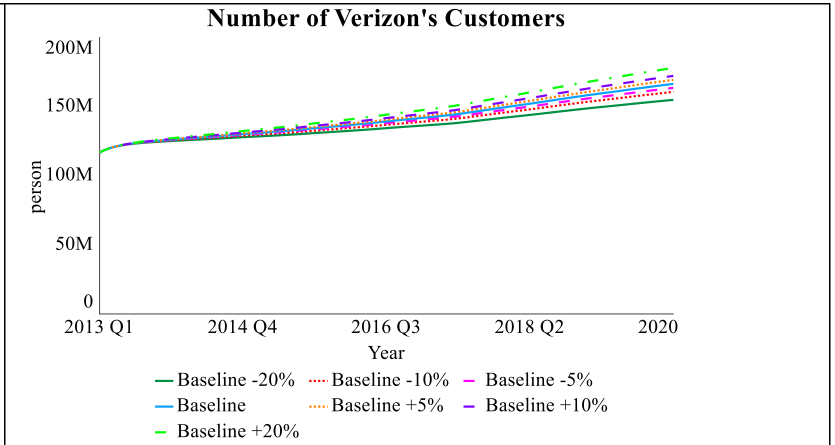
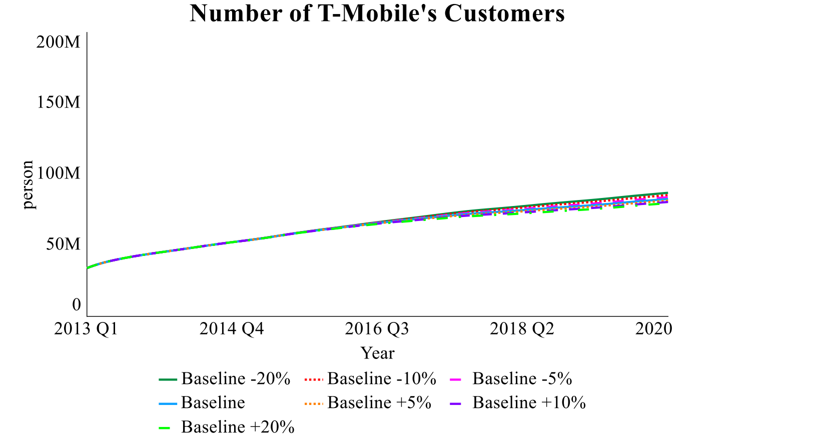
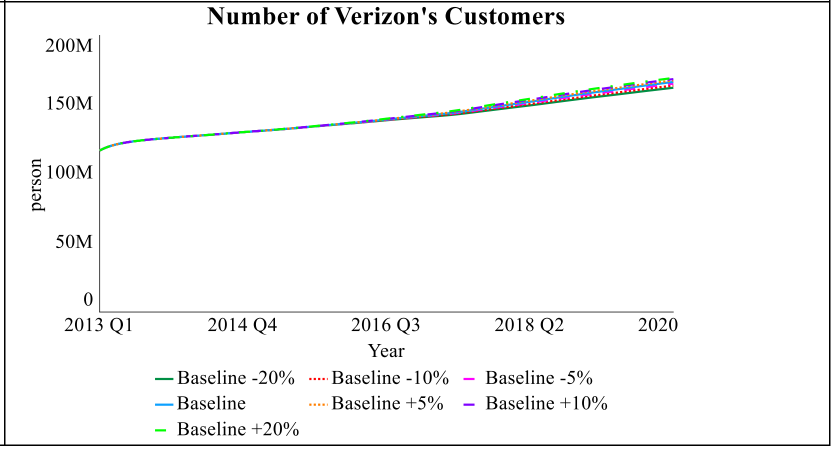
Base Productivity of Direct Marketing Investment	1	When the base productivity of direct market investment is maximal, the quality of direct marketing is maximized (hit rate is 1), meaning that customer acquisition only depends on product attractiveness. This explains why T-Mobile, with higher product attractiveness, was experiencing a steady growth of its customer base.		0	Same as the baseline (of which the base productivity of direct marketing investment is 0.5/10^9)	Same as baseline
Direct Marketing Hit Rate	1	When direct market hit rate is 1, all customers targeted will be exposed to direct marketing, meaning that customer acquisition depends mostly on product attractiveness. This explains why T-Mobile's market share is steadily developing during the simulation period.		0	When direct marketing hit rate is 0, there will be no customers exposed to direct marketing, meaning that direct marketing investments have no effect at all on customer acquisition. Thus, there is mostly no competitive advantage of Verizon in BDA investments. This explains the increasing trend of T-Mobile's market share.	
Reference Error Fraction	1	Same as the baseline	Same as the baseline	0	When the reference error fraction is 0, every prospective customer who is targeted will become subscriber. The effect of direct marketing expenditure on customer acquisition will eventually be higher, meaning that thought the total number of customers increases for both firms, Verizon will finally grow at a higher rate.	

Table 4. Extreme-Condition Test

b) *Behavior sensitivity test*

The purpose of this test is evaluate the sensitiveness of the model behavior toward each parameter (Barlas, 1996). The parameters by which the model behavior is largely affected will be used in the formulation of possible policy options. This test is conducted in two steps. First, all the selected parameters are tested. The resulting model behaviors are reported in Table 6. Table 6 reveals that the behavior of the system is mostly sensitive toward the following parameters: *Initial Potential Customers*, *Potential Market Growth Rate*, *Fraction of Investment in BDA*, *Fraction of Investment in Data Acquisition*, *Fraction of Marketing Expenditure*, *Price Elasticity*, and *Product Quality Elasticity*, compared to other parameters.

<table>
<tr><th rowspan="2">Parameter</th><th colspan="2">System Behavior</th></tr>
<tr><th>T-Mobile</th><th>Verizon</th></tr>
<tr><td>Initial Potential Customers (Baseline: 18,000,000)</td><td>
</td><td>
</td></tr>
</table>

Potential Market Growth Rate (Baseline: 0.06)		
Fraction of Investment in BDA (Baseline: 0.06)		

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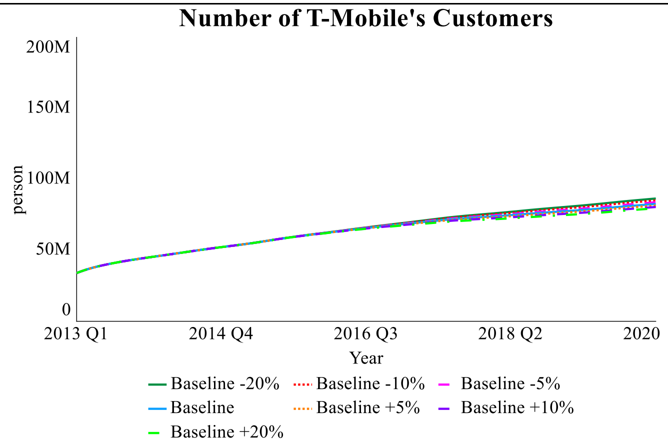
<tr>
<td>Fraction of Investment in Data Acquisition (Baseline: 0.05)</td>
<td>
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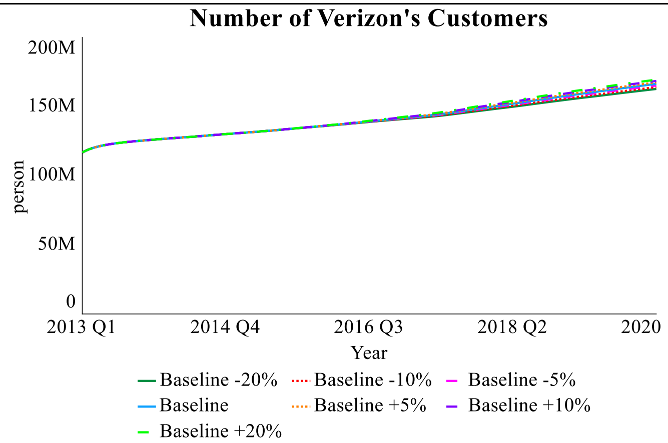
<td>
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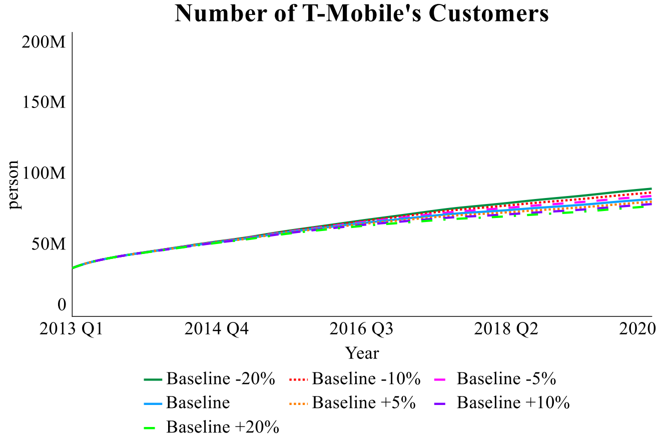
<tr>
<td>Fraction of Marketing Expenditure (Baseline: 0.2)</td>
<td>
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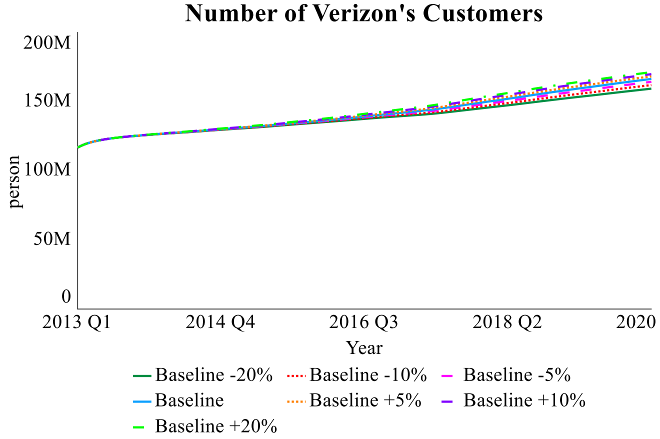
<td>
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<table>
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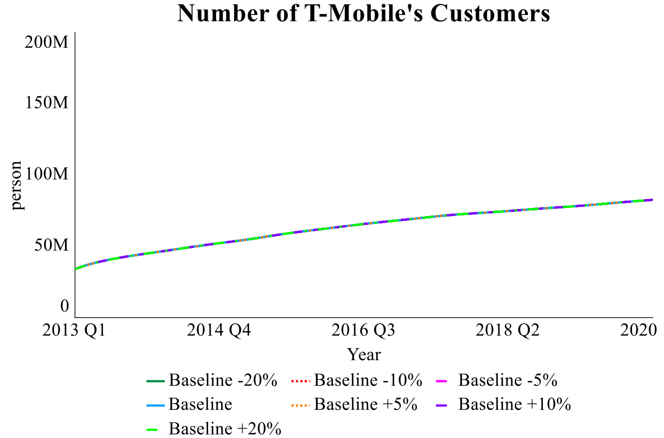
Investment in
Service
(Baseline: 0.25)</td>
<td>
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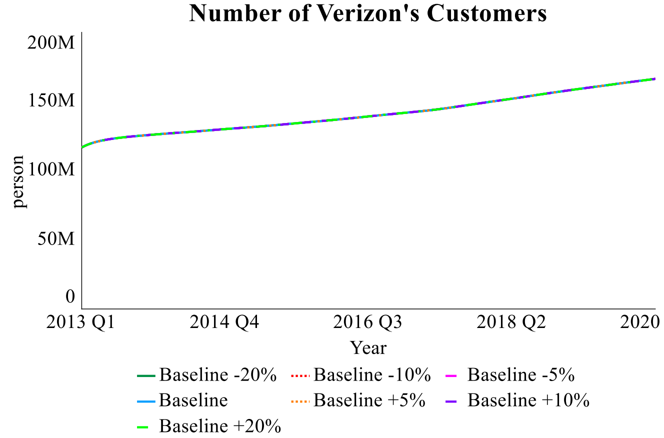
<td>
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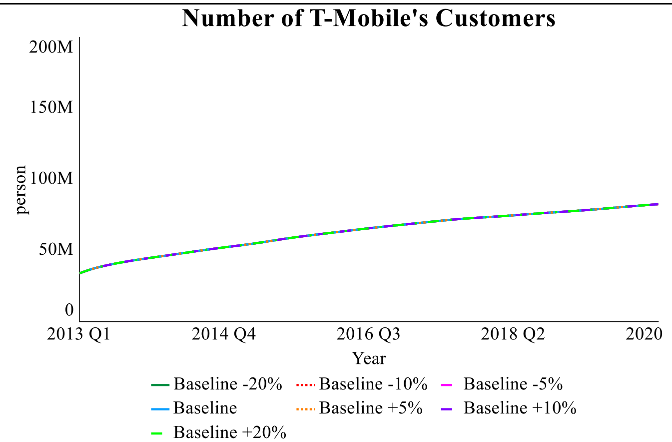
</tr>
<tr>
<td>Fraction of
Investment
in Hardware
(Software)
(Baseline: 0.1)</td>
<td>
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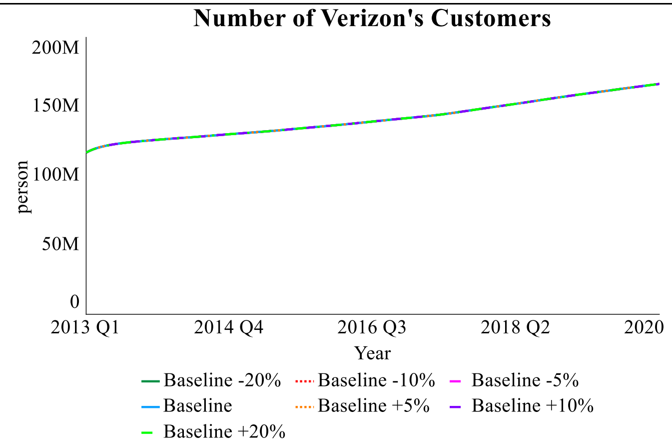
<td>
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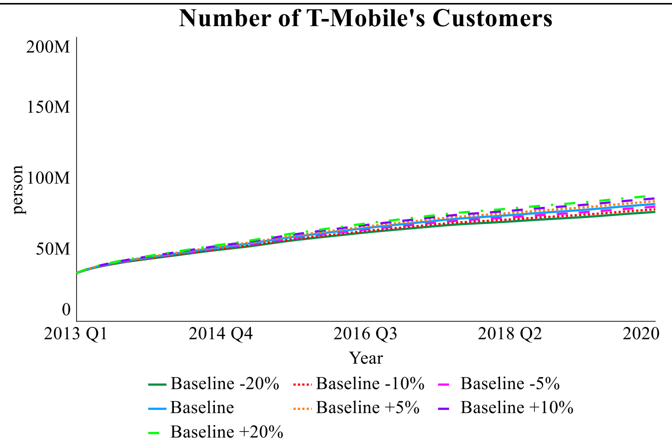
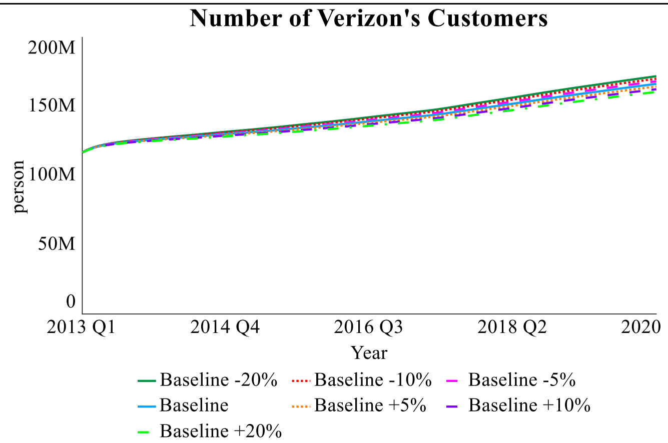
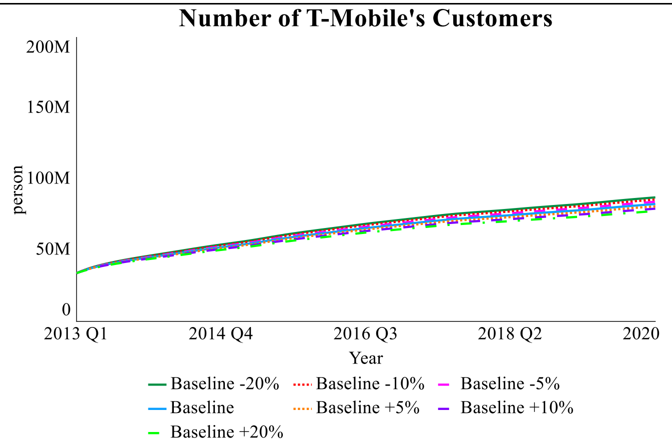
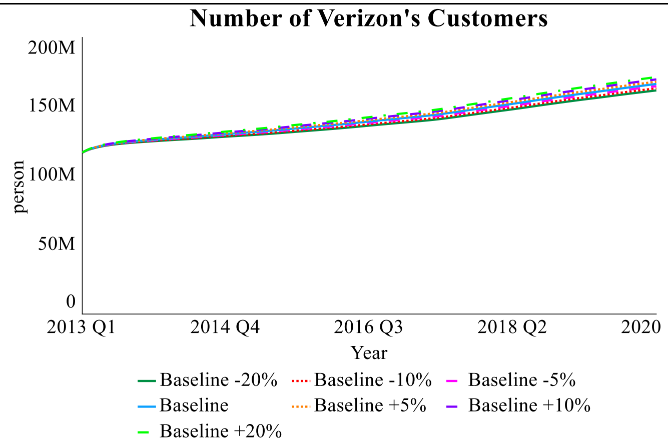
Price Elasticity (Baseline: -0.7)		
Product Quality Elasticity (Baseline: 0.47)		

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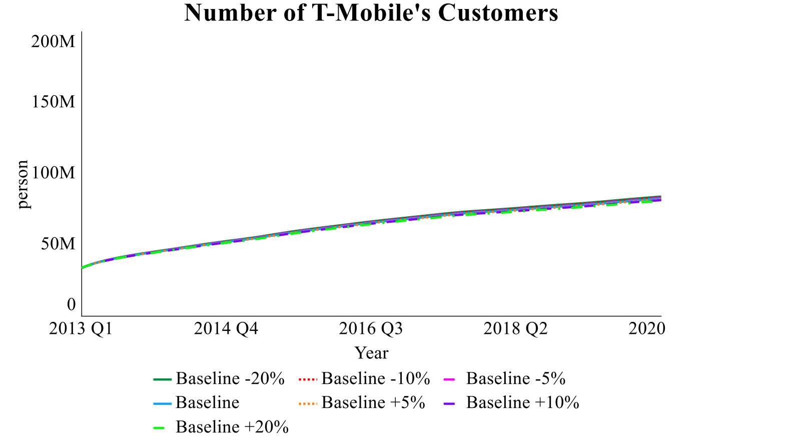
<td>
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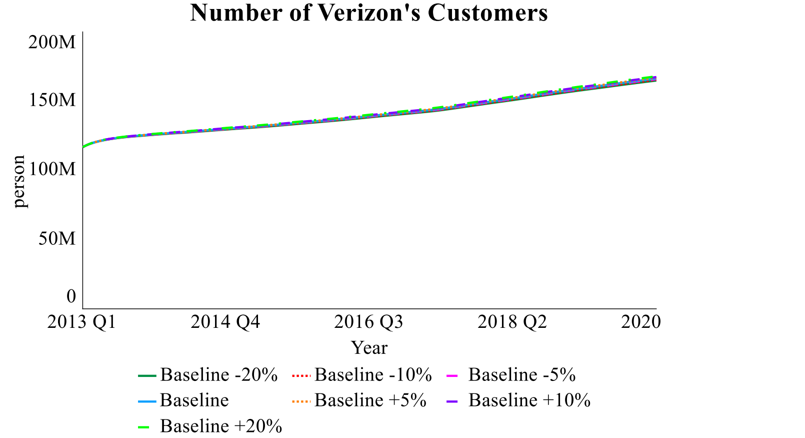
<td>
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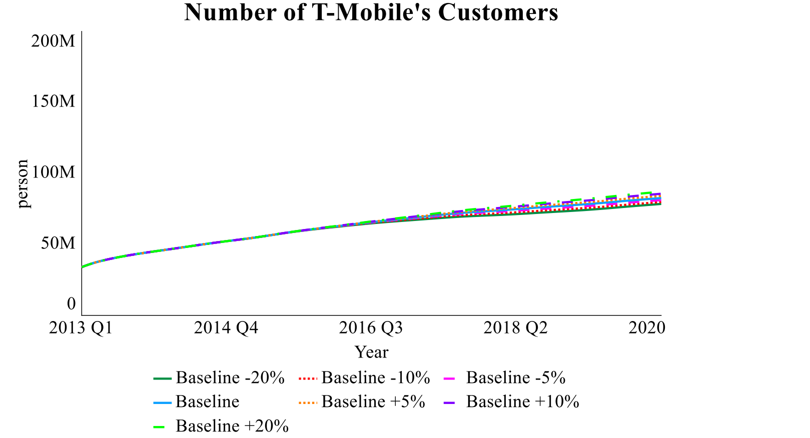
<td>Desired vs Basic Data Acquired

(Baseline: 4)</td>
<td>
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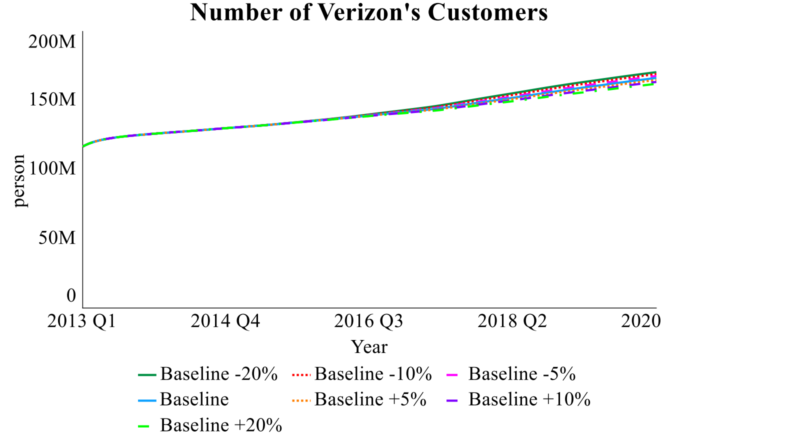
<td>
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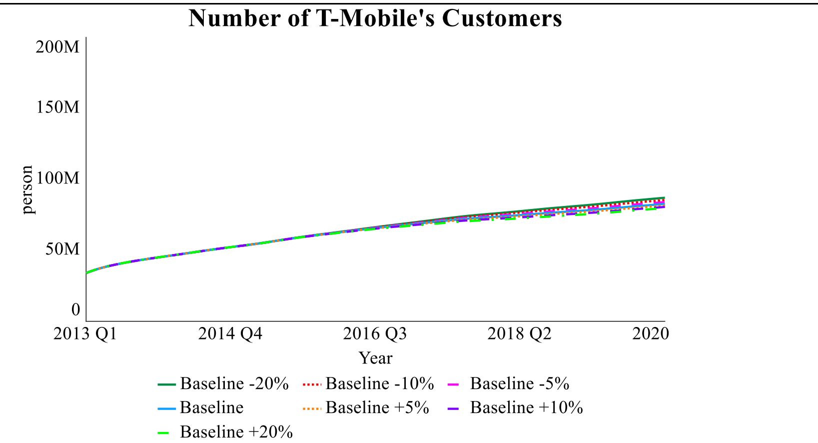
(Baseline: 0.06)</td>
<td>
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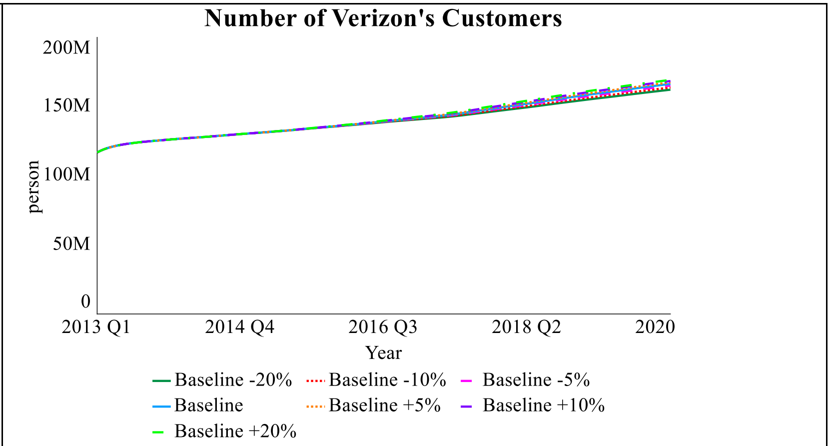
<td>
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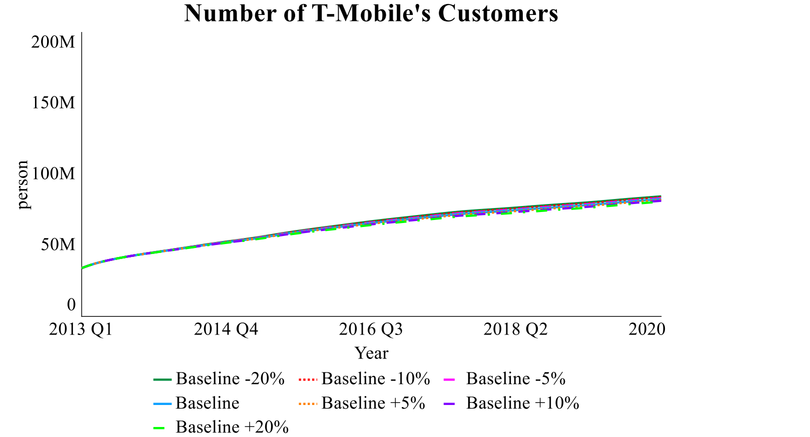
<td>
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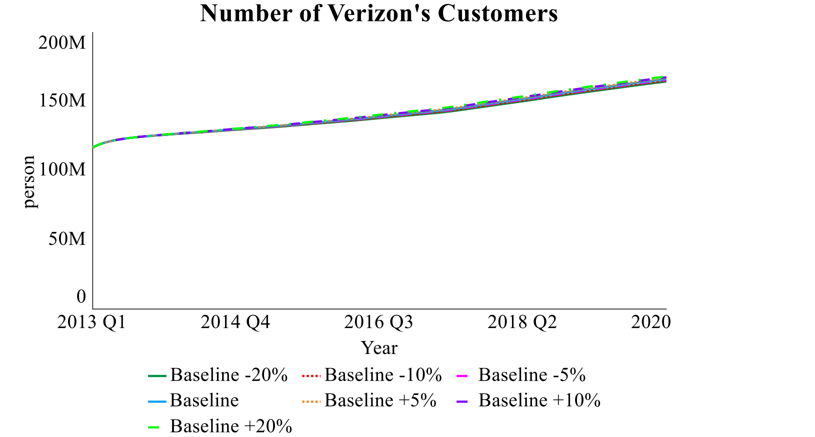
<td>
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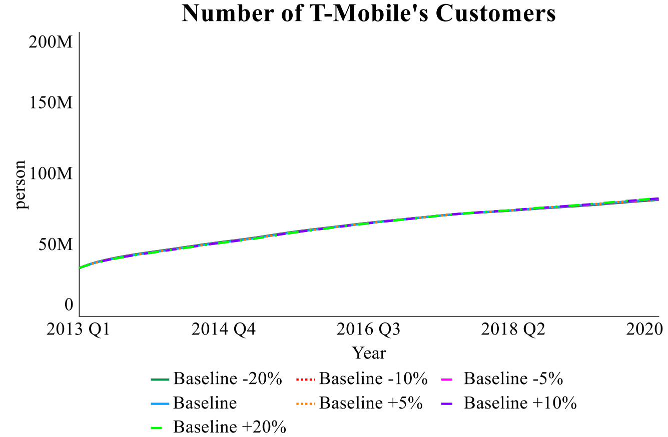
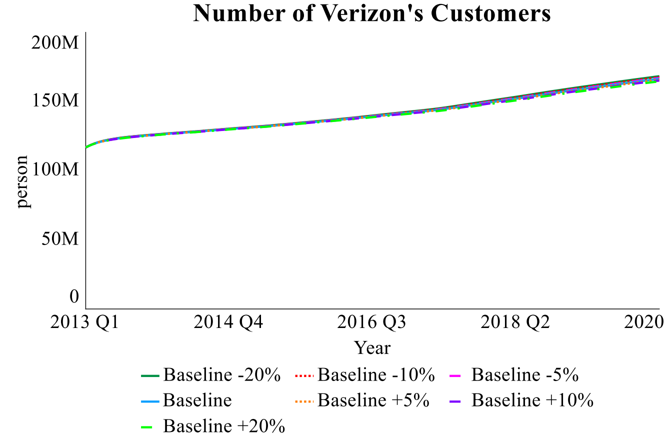
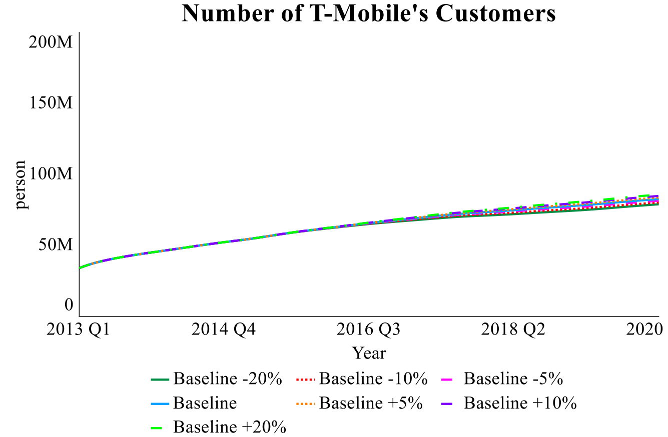
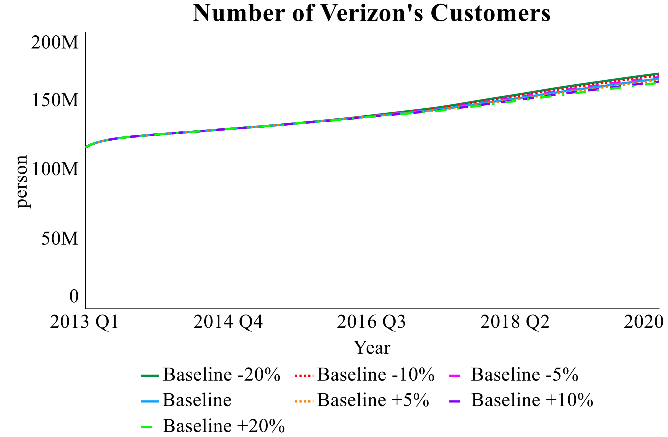
Time to Perceived Product Attractiveness (Baseline: 3)		
Reference Average Acquisition Cost per Extra Data Unit (Baseline: 3)		

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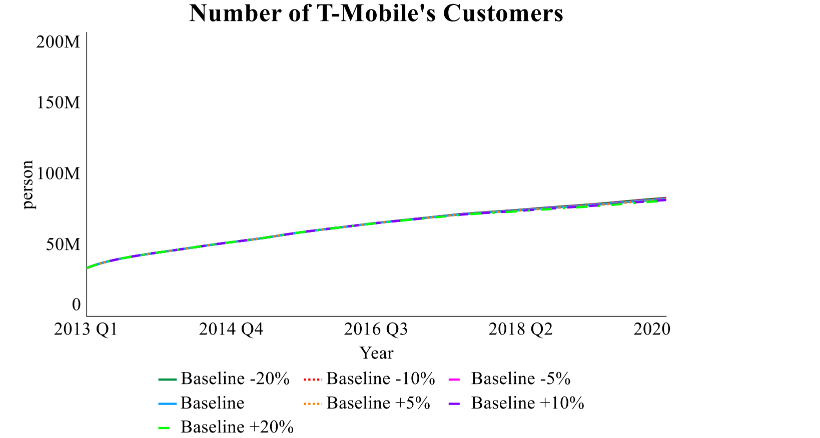
<td>Basic Data Acquired Per Customer Per Month

(Baseline: 1.7)</td>
<td>
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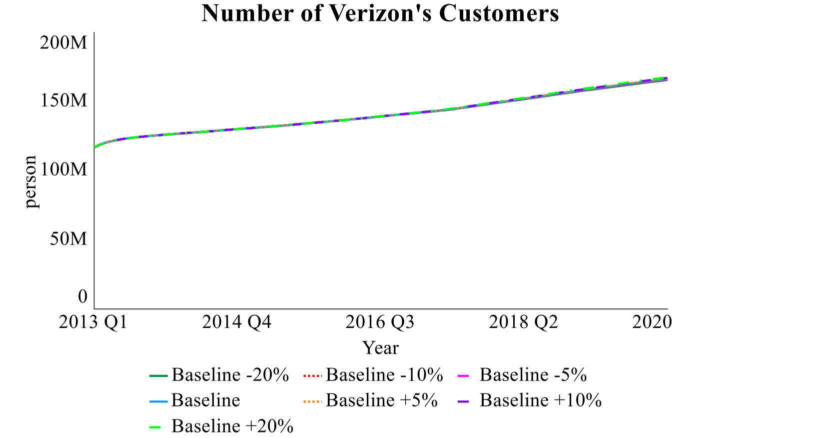
<td>
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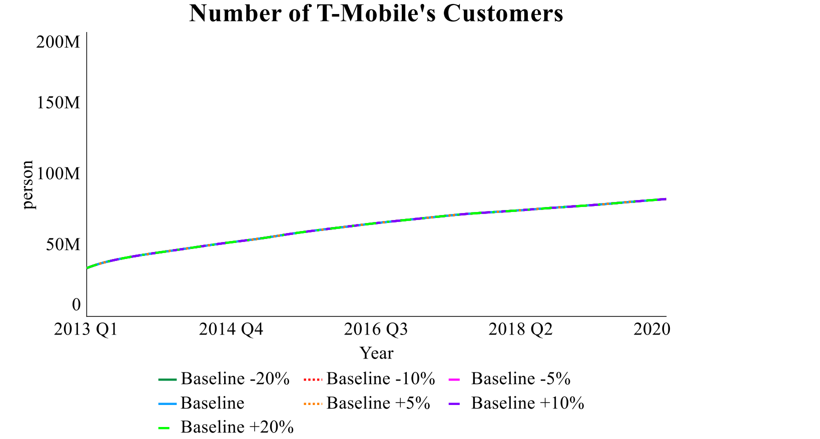
<td>Reference Storage Cost per Data Unit

(Baseline:</td>
<td>
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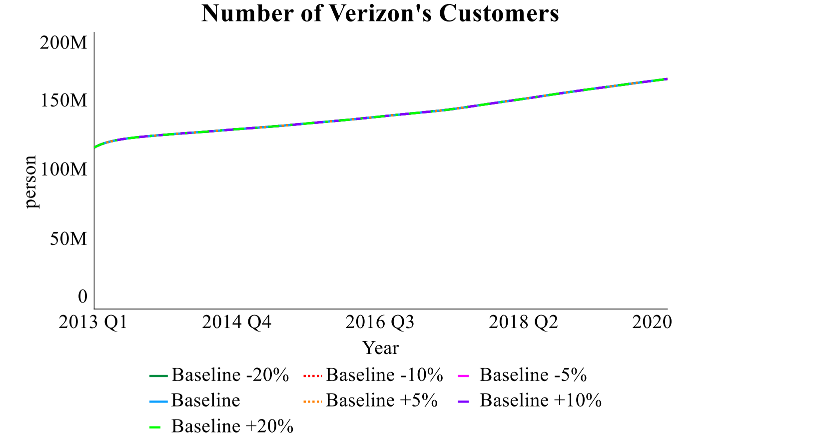
<td>
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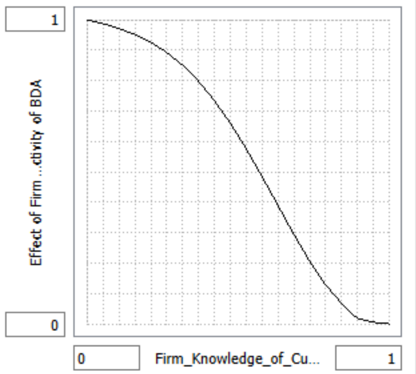
Table 5. Results of Parameter Behavior Sensitivity Test

Next, all graphical functions are tested. The results are reported in Table 7. This table reveals that the system behavior is the most sensitive toward the following graphical functions: *Effect of Quality of Direct Marketing on Productivity of Expenditure of Direct Marketing*, *Effect of Firm Knowledge Per Customer on Productivity of Direct Marketing Expenditure*, and *Effect of Data Volume on Productivity of BDA Investment* compared to the others.

In conclusion, the results of the behavior sensitivity test support my expectation that a change in BDA and data acquisition investments would lead to another significant change in the model behavior. This is important insight that will be used in Chapter 8 about policy option analysis.

<table>
<tr><th rowspan="2">Name</th><th colspan="2">Graphical Function</th><th rowspan="2">System Behavior</th></tr>
<tr><th>Baseline</th><th>Test</th></tr>
<tr>
<td>Effect of Firm Knowledge of Customers on Productivity of BDA</td>
<td></td>
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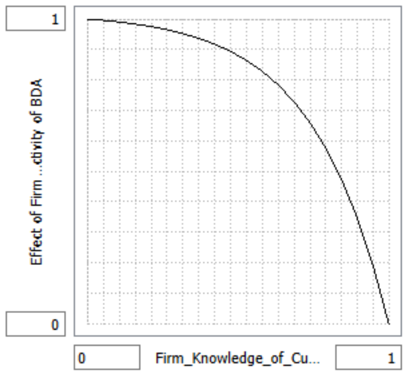
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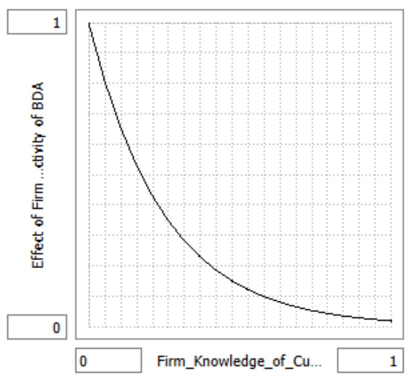</td>
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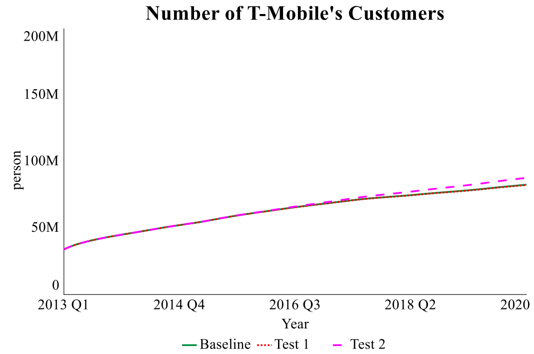
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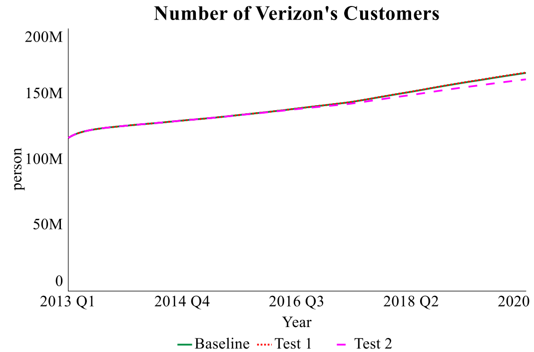</td>
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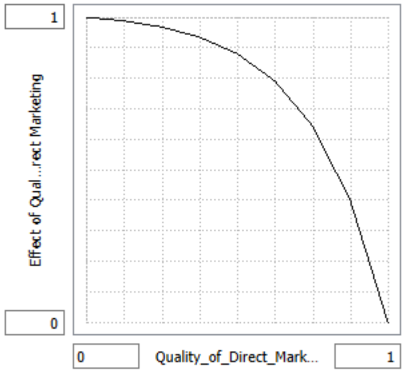
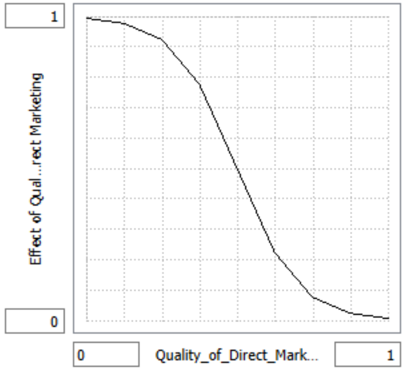
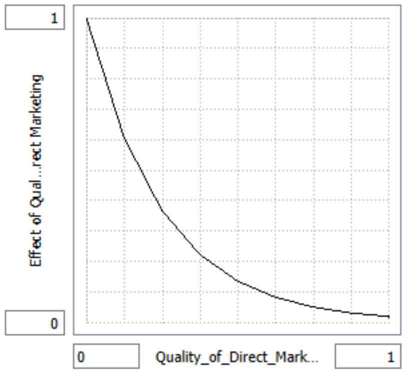
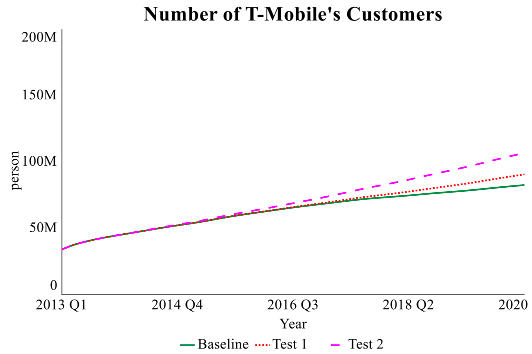
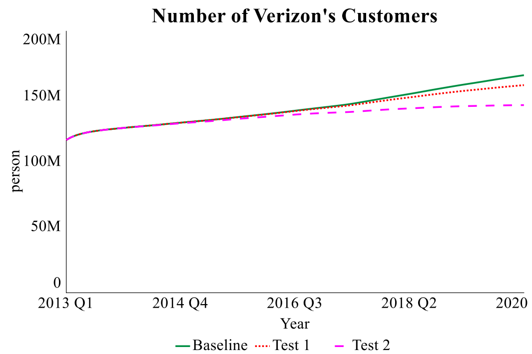
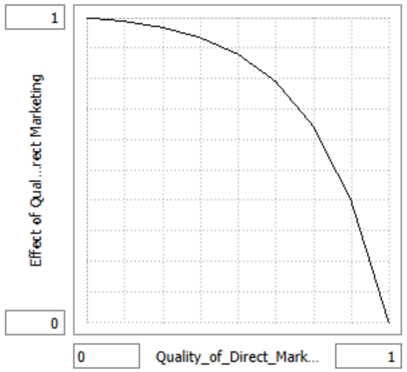
Effect of Quality of Direct Marketing on Productivity of Expenditure of Direct Marketing		- **Test 1**  - **Test 2** 	- **T-Mobile**  - **Verizon** 

Effect of Firm Knowledge Per Customer on Productivity of Direct Marketing Expenditure



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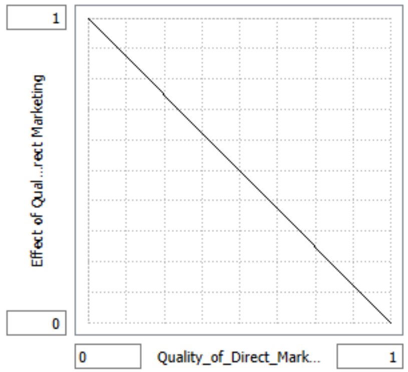

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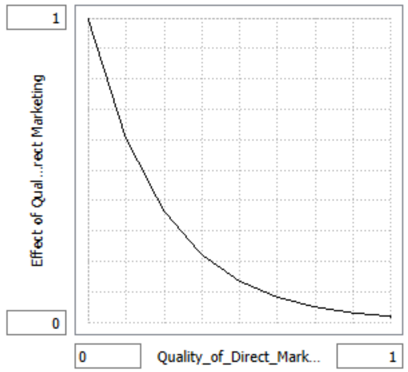

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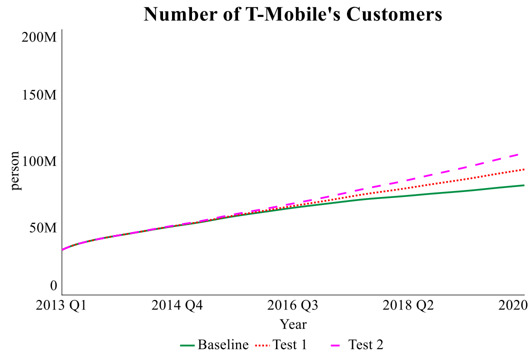

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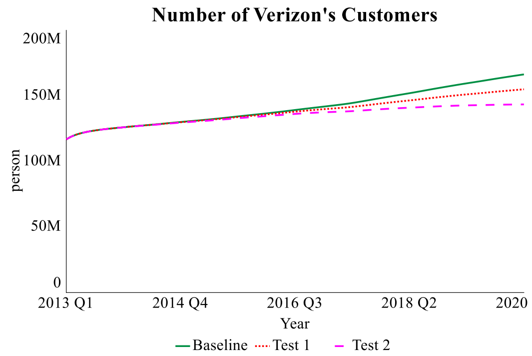

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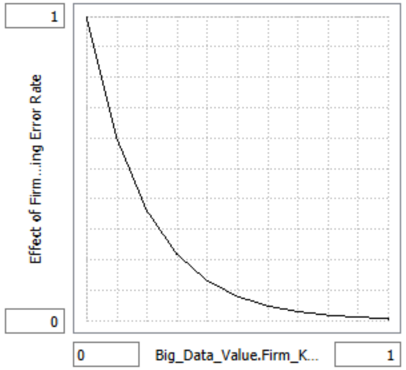
<td>
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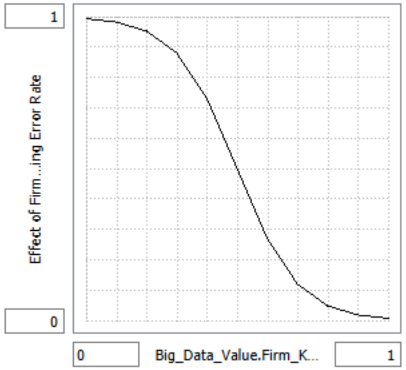

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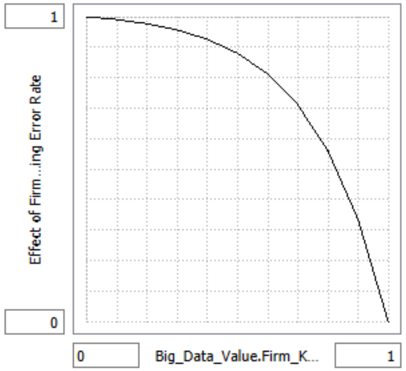
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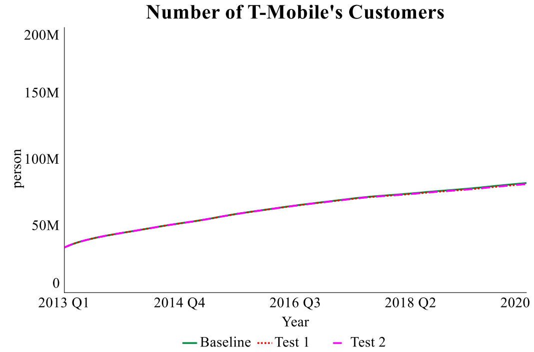

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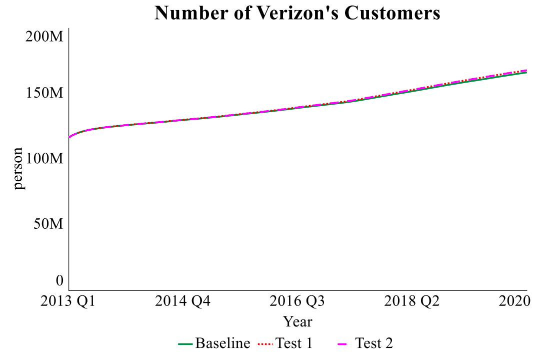
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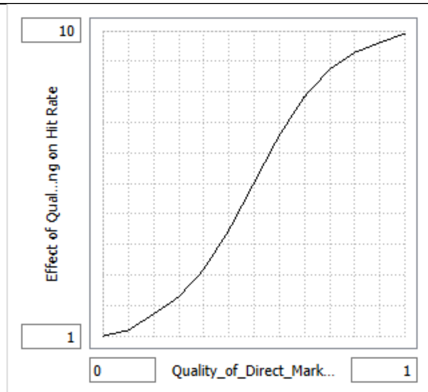
<td>
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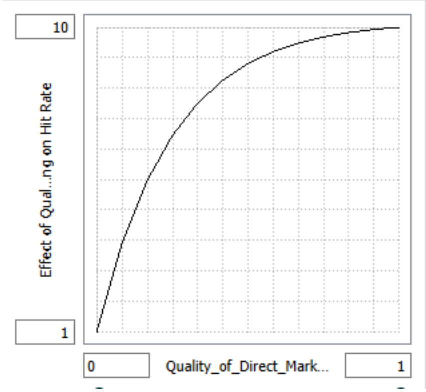

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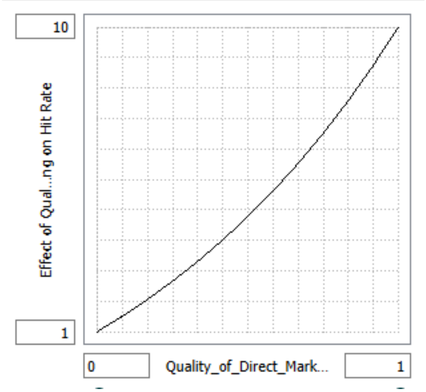
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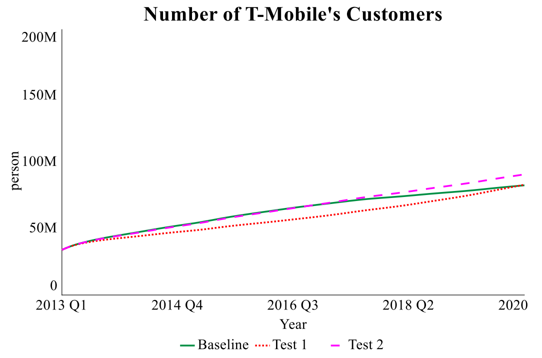

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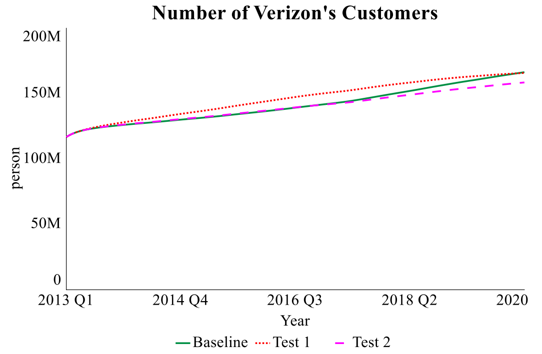
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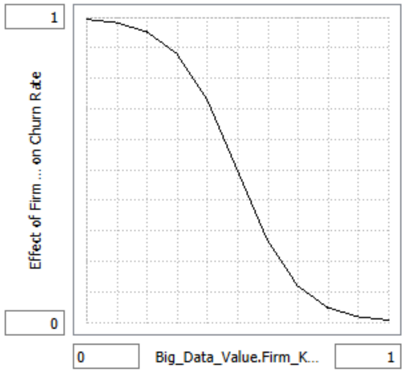
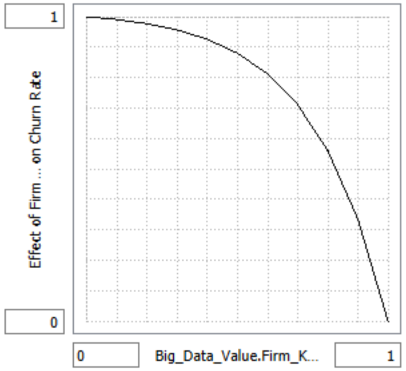
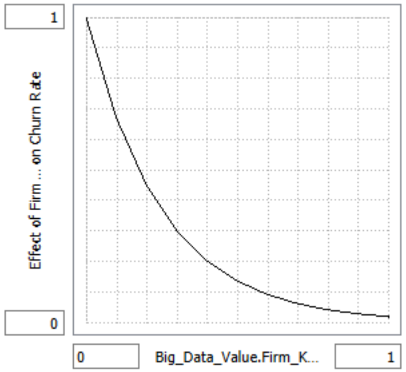
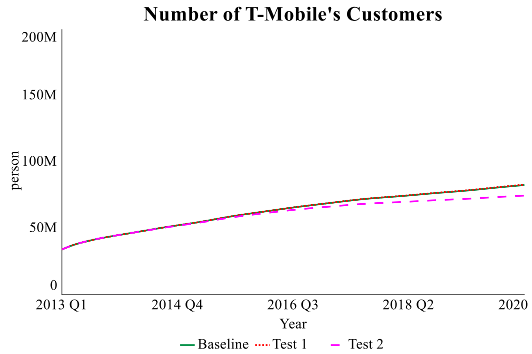
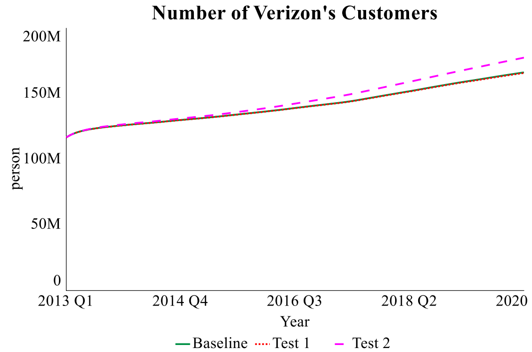
Effect of Firm Understanding of Customers on Churn Rate	 	- **Test 1**  - **Test 2**  	- **T-Mobile**  - **Verizon** 

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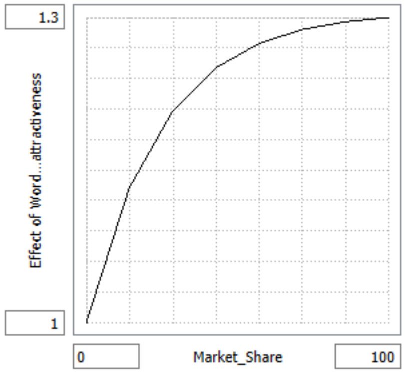
<td>
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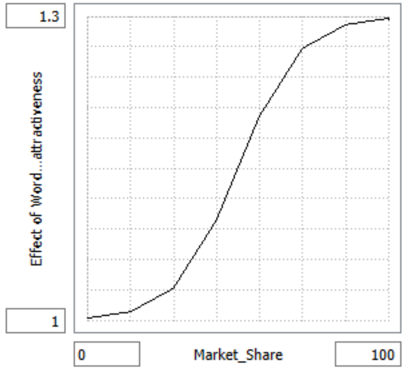

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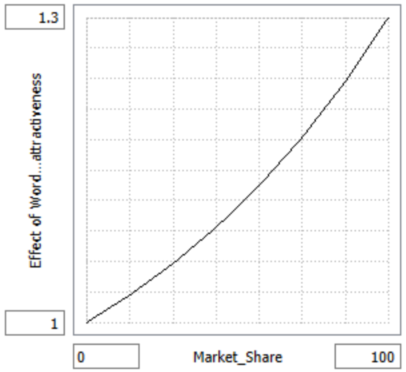
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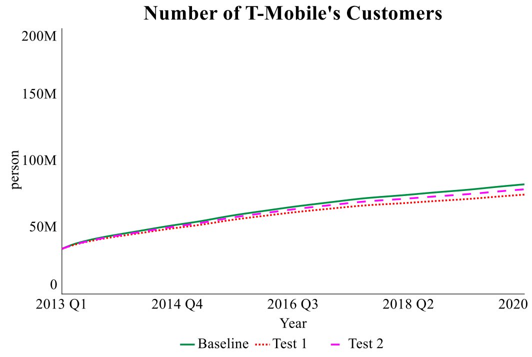

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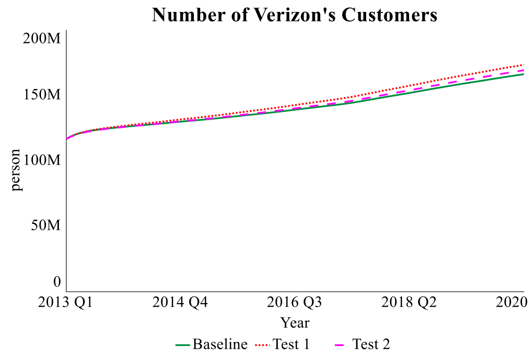
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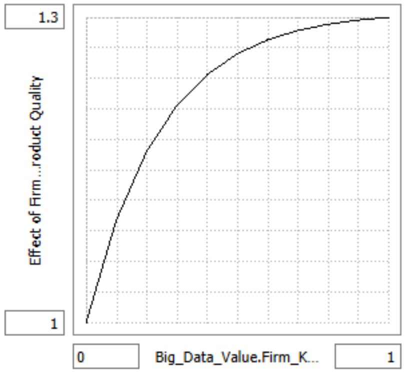
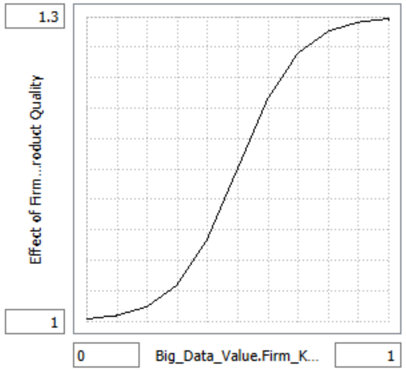
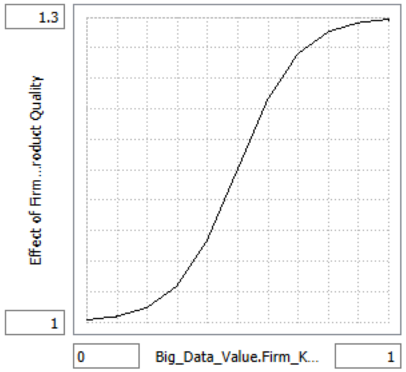
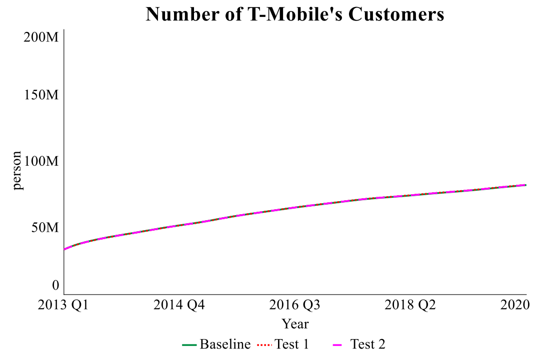
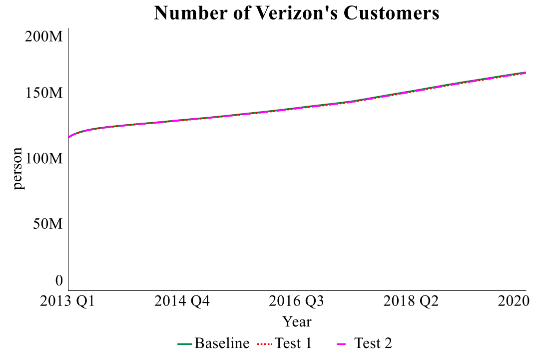
Effect of Firm Knowledge of Customers on Product Quality		- **Test 1**  - **Test 2** 	- **T-Mobile**  - **Verizon** 

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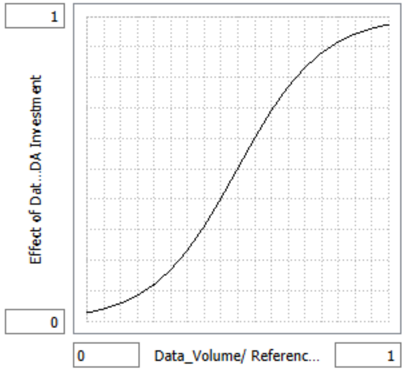

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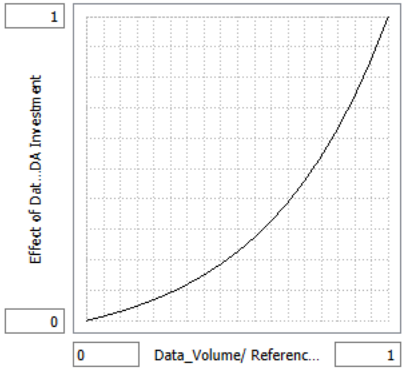

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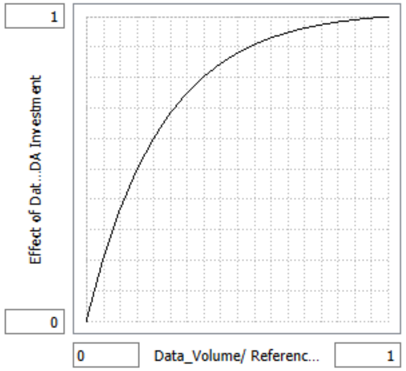

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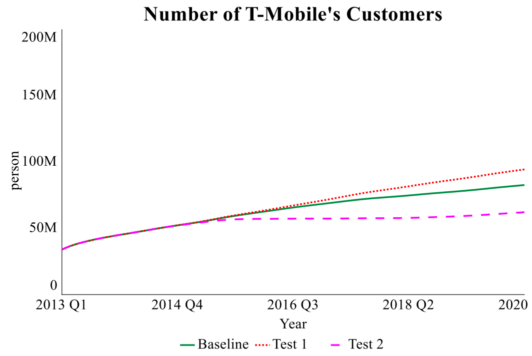

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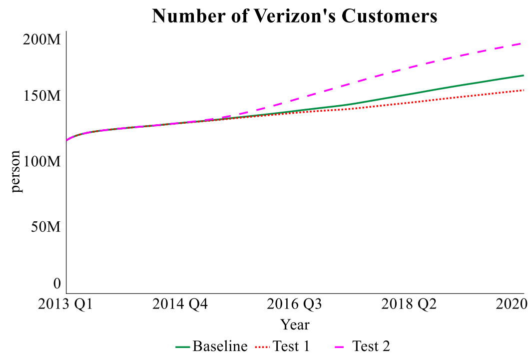

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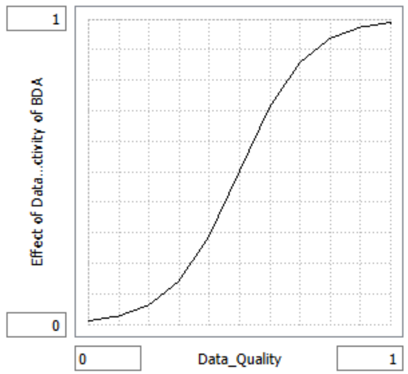
<td>
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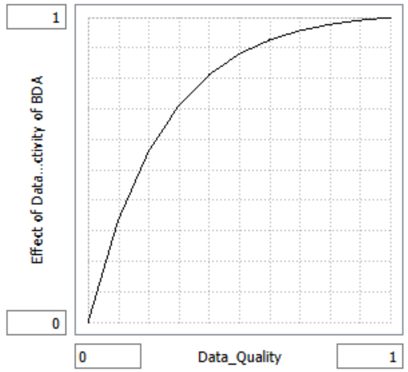

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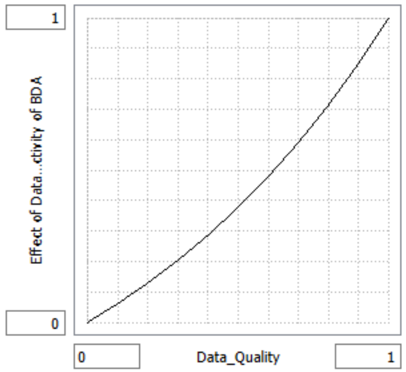
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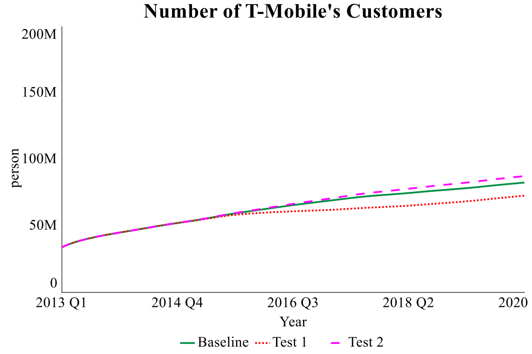

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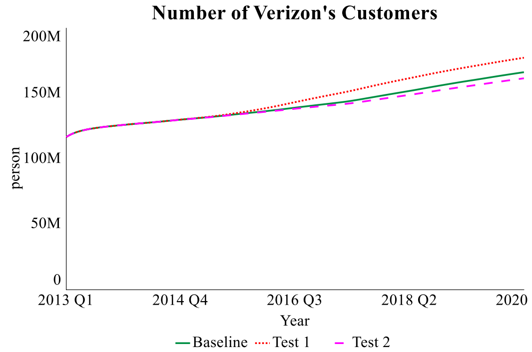
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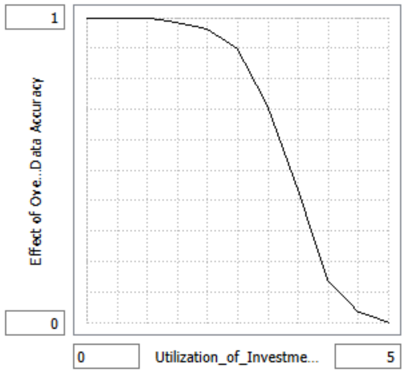
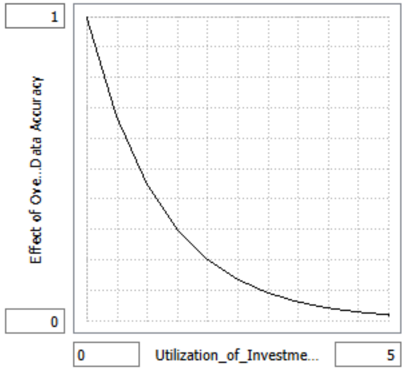
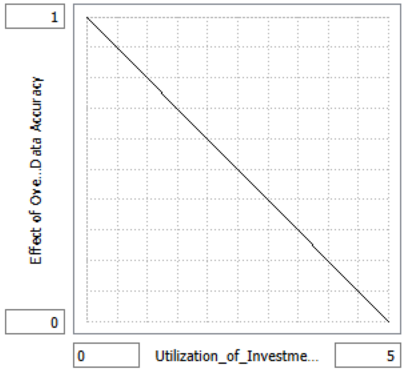
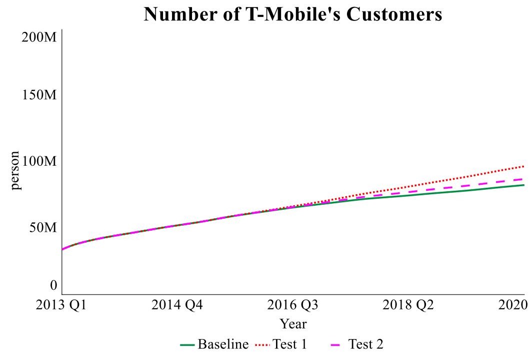
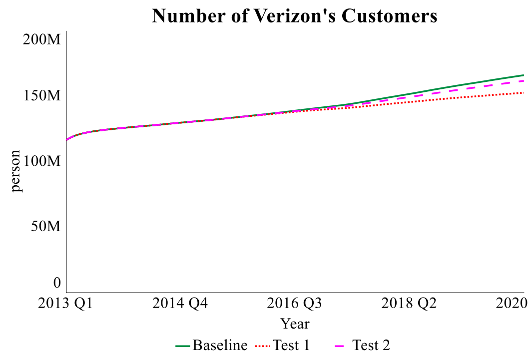
Effect of Over Utilization of Investment in Database Completeness Per Customer on Data Accuracy	 	- **Test 1**  - **Test 2**  	- **T-Mobile**  - **Verizon** 

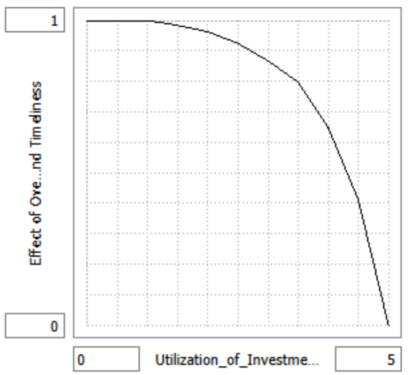
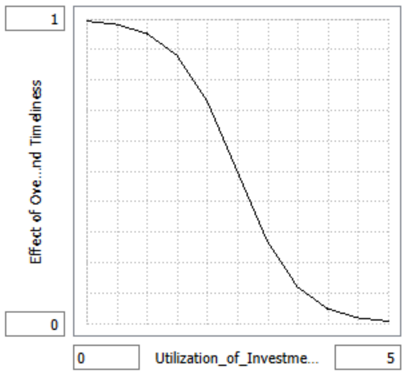
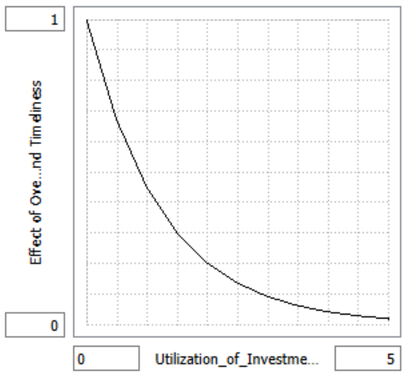
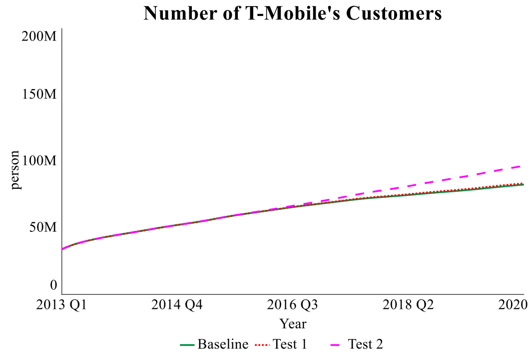
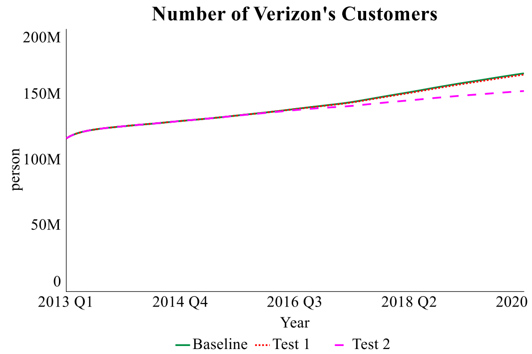
Effect of Over Utilization of Investment in Database Completeness Per Customer on Data Consistency and Timeliness		- **Test 1**  - **Test 2** 	- **T-Mobile**  - **Verizon** 

Table 6. Results of Graphical Function Behavior Sensitivity Test

c) Integration error tests

As stated by J. Sterman (2000), a good system dynamics model should not have results that are sensitive to the choice of time step (DT) or numerical integration method. Currently the SD model of this thesis is run using the Euler integration method with time step (DT) equal to 0.25. In this part, I rerun the model using two different integration methods, namely the Euler and RK4 approaches. In addition, different time steps (DTs) are used, including 1, 1/2, 1/4, 1/8, and 1/16. As shown in Figure 15, the test results show that the main model behavior, number of total customers, does not establish significantly different patterns over the different values of DT and integration methods for both T-Mobile and Verizon.

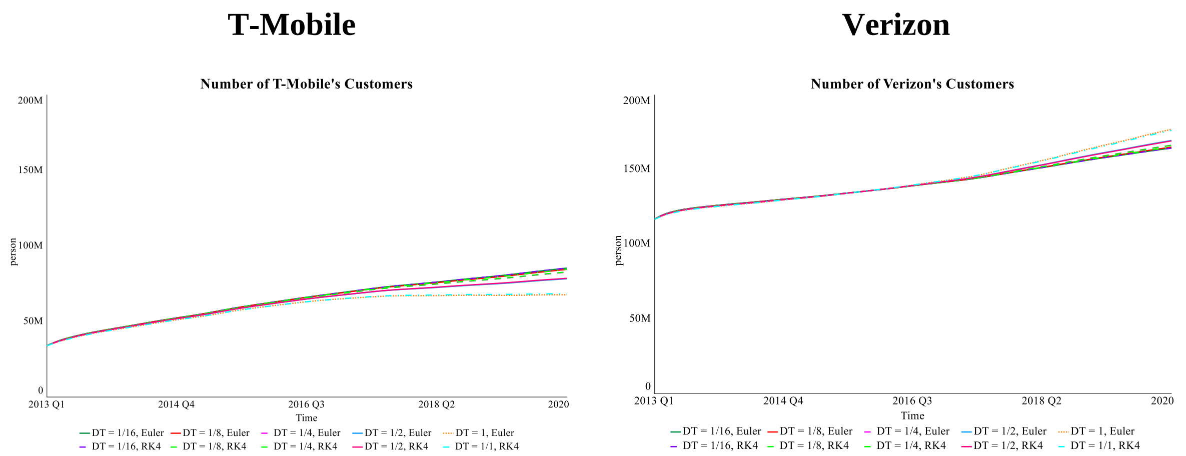


Figure 15. Results of Integration Error Tests

6.3 Behavior Validity: Behavior Pattern Tests

While the above tests focus on the validity of the model structure, this set of behavior pattern tests aims to check whether the model can precisely reproduce the pattern of the observed behaviors (Barlas, 1996).

Based on the results of model calibration (see Chapter 5), the observed numbers of customers of T-Mobile and Verizon were reproduced as shown in Figure 16 below. Visual inspection shows that the reference mode was properly reproduced by the model. I also perform a more formal test of the model fit using Root-Mean-Square Percent Error (RMSPE) and Theil inequality statistics suggested by John D Sterman (1984). While RMSPE refers to a normalized measure of error, U^M, U^S, and U^C represent the fraction of the mean-square-error (MSE) due to bias, unequal variance, and unequal covariance, respectively (John D Sterman, 1984). As shown in Table 7, my results show that RMSPE of the total number of customers for both firms are lower than .01, indicating a good fit between simulated and observed behaviors (Khan et al., 2020; John D Sterman, 1984). Furthermore, for T-Mobile, 57% of MSE is caused by bias, 43% of MSE is due to unequal covariance, and 0.3% of MSE is due to unequal variance. For Verizon, 0.8% of MSE is due to bias, 0.4% is due to unequal variance, and almost 100% of MSE is due to unequal covariance.

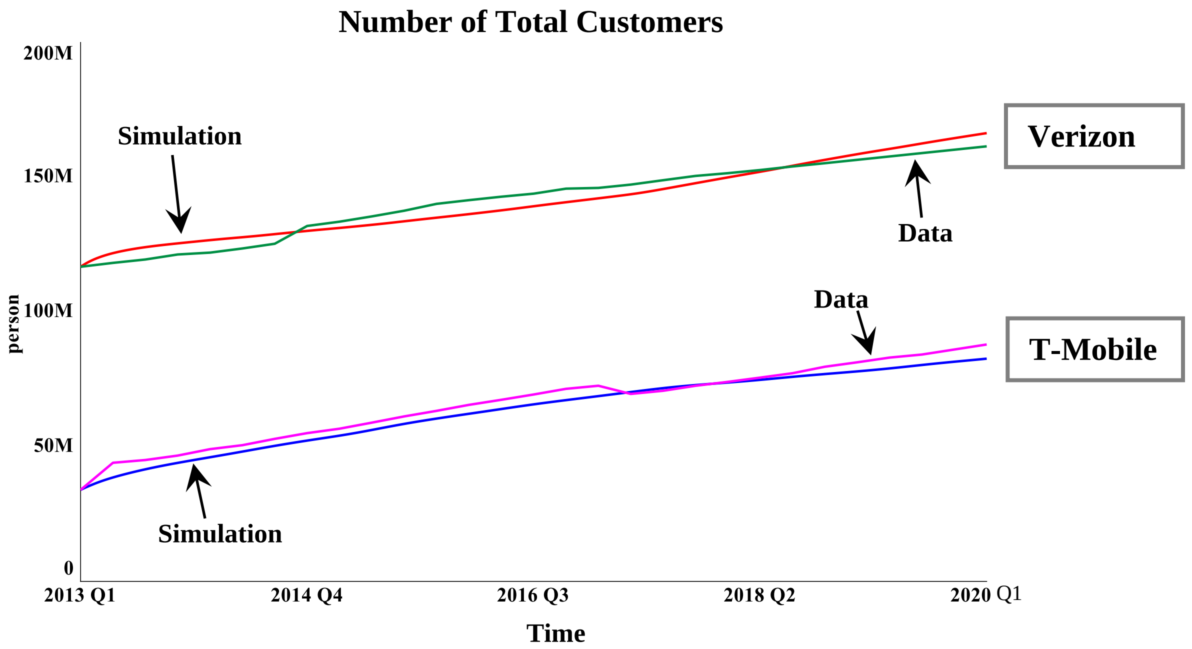


Figure 16. Simulation Results Behavior Against Historical Data – Number of Customers

With regards to the firm revenue, Figure 17 shows that my model seems to reasonably replicate the observed behaviors for both firms. Indeed, as shown in Table 7, RMSPE is lower than .01 for both firms, meaning that the simulated behavior fits well with the observed one. For T-Mobile, 87% of MSE is due to bias, 2.2% of MSE is due to unequal variance, and 10.6% of MSE is due to unequal covariance. For Verizon, 74.3% of MSE is due to bias, 0.1% of this error is due to unequal variance, and 25.9% of MSE is due to unequal covariance.

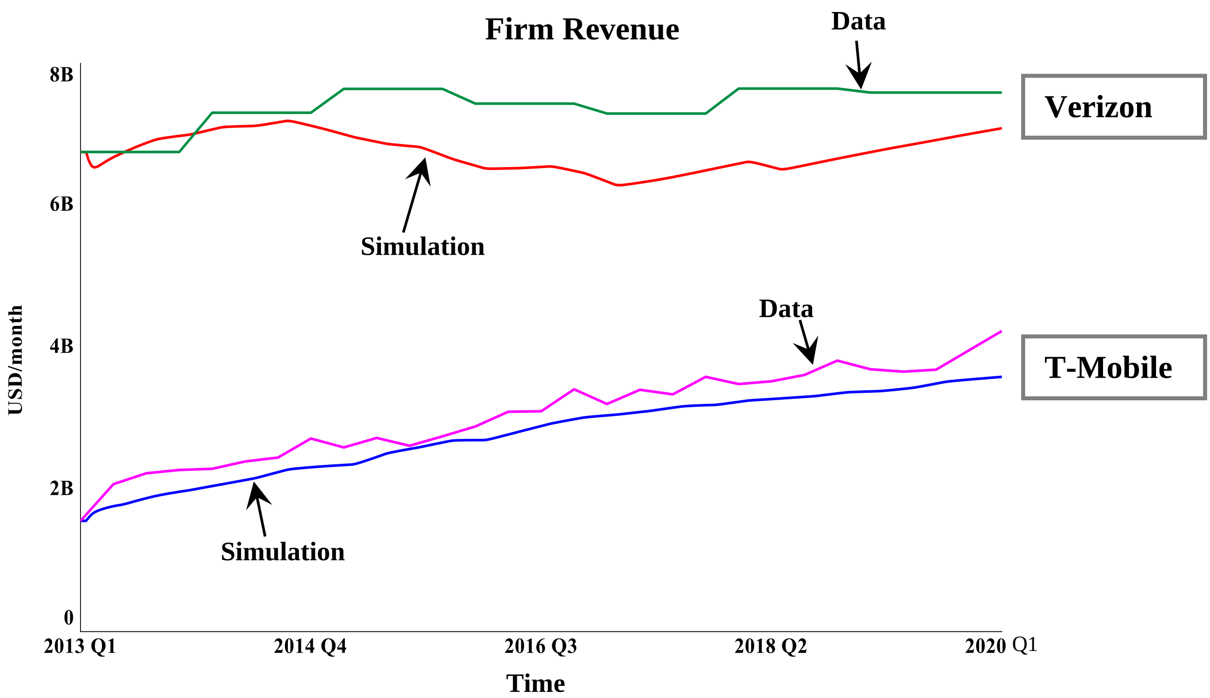


Figure 17. Simulation Results Behavior Against Historical Data – Firm Revenue

Finally, with regards to firm profit, Figure 18 shows that my model reasonably replicates the observed behaviors for both firms. However, RMSPE is very high (larger than 1) for T-Mobile as the simulated profit is much higher than the observed one at the beginning. As I focus on replicating the trend rather than the points, RMSPE is recomputed with the first 27 data points removed for T-Mobile. The new results show that RMSPE is 0.11 for T-Mobile and 0.03 for Verizon, indicating that the model obtains adequate fit. For T-Mobile, 3.2% of MSE is due to bias, 91.3% of MSE is due to unequal variance, and 7.2% of MSE is due to unequal covariance. For Verizon, 0.1% of MSE is due to bias, 10.9% of this error is due to unequal variance, and 90.2% of MSE is due to unequal covariance. As the major portion of error magnitude diverges between the behaviors, I focus on the value of RMSPE to conclude that the simulated behaviors adequately reproduce the observed trends.

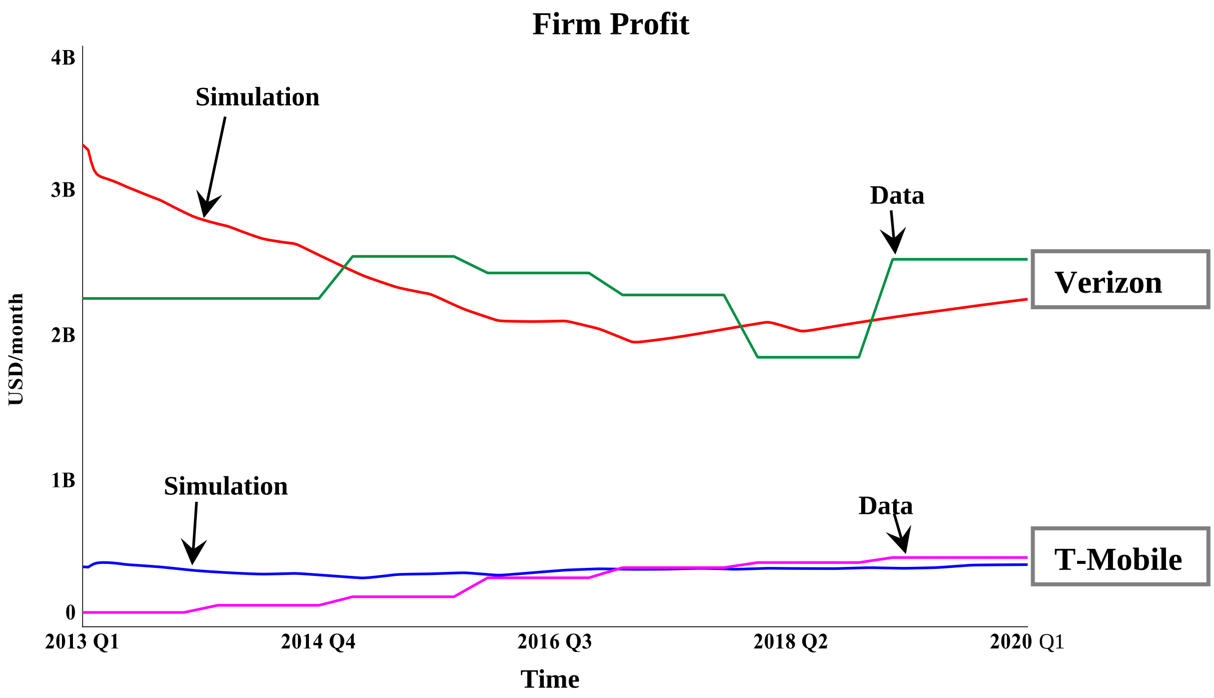


Figure 18. Simulation Results Behavior Against Historical Data – Firm Profit

Variable	RMSPE	MSE (units)	U^m	U^S	U^C
Number of customers T-Mobile	0.001	5.607E+12	0.572	0.003	0.429
Number of customers Verizon	0.001	1.297E+13	0.008	0.004	1.00
Firm revenue T-Mobile	0.009	8.640E+16	0.873	0.022	0.106
Firm revenue Verizon	0.010	5.630E+17	0.743	0.001	0.259
Firm profit T-Mobile	0.109	5.821E+15	0.032	0.913	0.072
Firm profit Verizon	0.030	1.568E+17	0.001	0.109	0.902

Table 7. Model Goodness of Fits to Historical Data (Error Analysis)

Chapter 7: Scenario Analysis

7.1 Scenario Analysis Overview

In this chapter, I present results of my analysis of different market scenarios. Scenario analysis is used to investigate how the model behaviors would change when different environmental conditions would arise (J. Sterman, 2000), which prepares firms to deal with the turbulence of external factors and respond to it in a timely manner (Khan et al., 2020). As mentioned above, the impact of investments in BDA on firm performance is largely affected by the size of the firm's customer base. For example, bigger data volume is expected to lead to higher productivity of BDA activities, and therefore, higher benefits of BDA investments. Nevertheless, bigger data volume implies higher expense on data storage cost, leading to lower net profit of the firm. This intriguing trade-off to firms is, however, subject to the future of BDA use in the whole industry, which is mostly out of the firm's control. In this thesis, two opposite scenarios are built to reflect this uncertainty in the development of BDA in the whole industry. The scenarios are developed using three exogeneous variables related to big data: Basic Data Acquired Per Customer Per Month, Reference Average Acquisition Cost Per Extra Data Unit, and Reference Storage Cost Per Data Unit. Table 8 describes the settings of the scenarios used in this chapter.

Scenarios	Variable	Change
BDA Explosion	- Basic Data Acquired Per Customer Per Month	50% growth
	- Reference Average Acquisition Cost Per Extra Data Unit	50% decline
	- Reference Storage Cost Per Data Unit	50% decline
Reference mode	- Basic Data Acquired Per Customer Per Month	0% change
	- Reference Average Acquisition Cost Per Extra Data Unit	0% change
	- Reference Storage Cost Per Data Unit	0% change
BDA Winter	- Basic Data Acquired Per Customer Per Month	50% decline
	- Reference Average Acquisition Cost Per Extra Data Unit	50% growth
	- Reference Storage Cost Per Data Unit	50% growth

Table 8. Scenario Settings

The first scenario, BDA Explosion, refers to situations favoring the use of big data and BDA. More particularly, existing evidence shows that the amount of data generated by people is rapidly increasing as people spend more time staying online (Petrov, 2020). Thus, with the development of more advanced technologies, one can expect that firms could collect more data from each of their new customers. In addition to the rise of big data, there would be more firms offering data storage services (e.g., cloud-based warehouse, etc.), and more technologies developed to optimize the data collection process (e.g., online data collection platforms, etc.). This leads to the reduction in the average costs of data acquisition and data storage.

In contrast, the second scenario, BDA Winter, refers to the prospect of decline in the use of and interest in big data and BDA. This expectation is founded based on two important issues: privacy issue and the limitation of (deep) machine learning. First, data privacy is one of the most important issues for customers nowadays. Indeed, more than 90% of American online consumers are concerned about their information privacy (TRUSTe, 2016). Examples of customers' concerns include firms exploiting their collected information to target customers' friends and family or selling the collected data to other firms so that customers would receive unwanted advertising materials or be treated unfairly. Consequently, consumers might refuse to share the information, or even refuse to use the products/services altogether. For example, 36% of online customers stop using a specific website or 29% stop using an app due to their privacy concern (TRUSTe, 2016).

Second, the development of BDA largely depends on the advancement in machine learning techniques, and especially deep learning algorithms. Nevertheless, while the use of deep learning (or artificial intelligence) is still currently increasing, there is now growing concern in the community such that firms might not be able to scale deep learning as effortlessly as they though (e.g., no more benefits when data volume increases), and machines might not be as intelligent as we think they should be (e.g., they can only learn what we want them to learn) (Piekniewski, 2018). If people start losing their interest in deep learning, their interest in big data and BDA would also be decreasing. In short, in the BDA Winter scenario, I suggest that firms would acquire less data from each of their new customers due to privacy issues, while the average costs of data acquisition and data storage increase due to less interest in the development of big data technologies and BDA.

7.2 Results of Scenario Analysis

The results of the scenario analysis show that an increase in the amount of data acquired per each customer and a decrease in the data storage and acquisition cost (BDA Explosion) leads to an increase in the number of total customers and market share for Verizon but a decrease in the number of customers and market share for T-Mobile (see Figure 19). In addition, the total revenue and profit of Verizon increase, while T-Mobile sees a decrease in revenue and a slight increase in profit (see Figure 20).

In contrast, as shown in Figure 19, a decrease in the amount of data acquired per each customer and an increase in the data storage and acquisition cost (BDA Winter) leads to a decrease in the number of total customers and market share for Verizon but an increase in the number of customers and market share for T-Mobile. In addition, Figure 20 shows that in this scenario, the total revenue and profit of T-Mobile increase, while Verizon sees a decrease in revenue and a slight increase in profit.

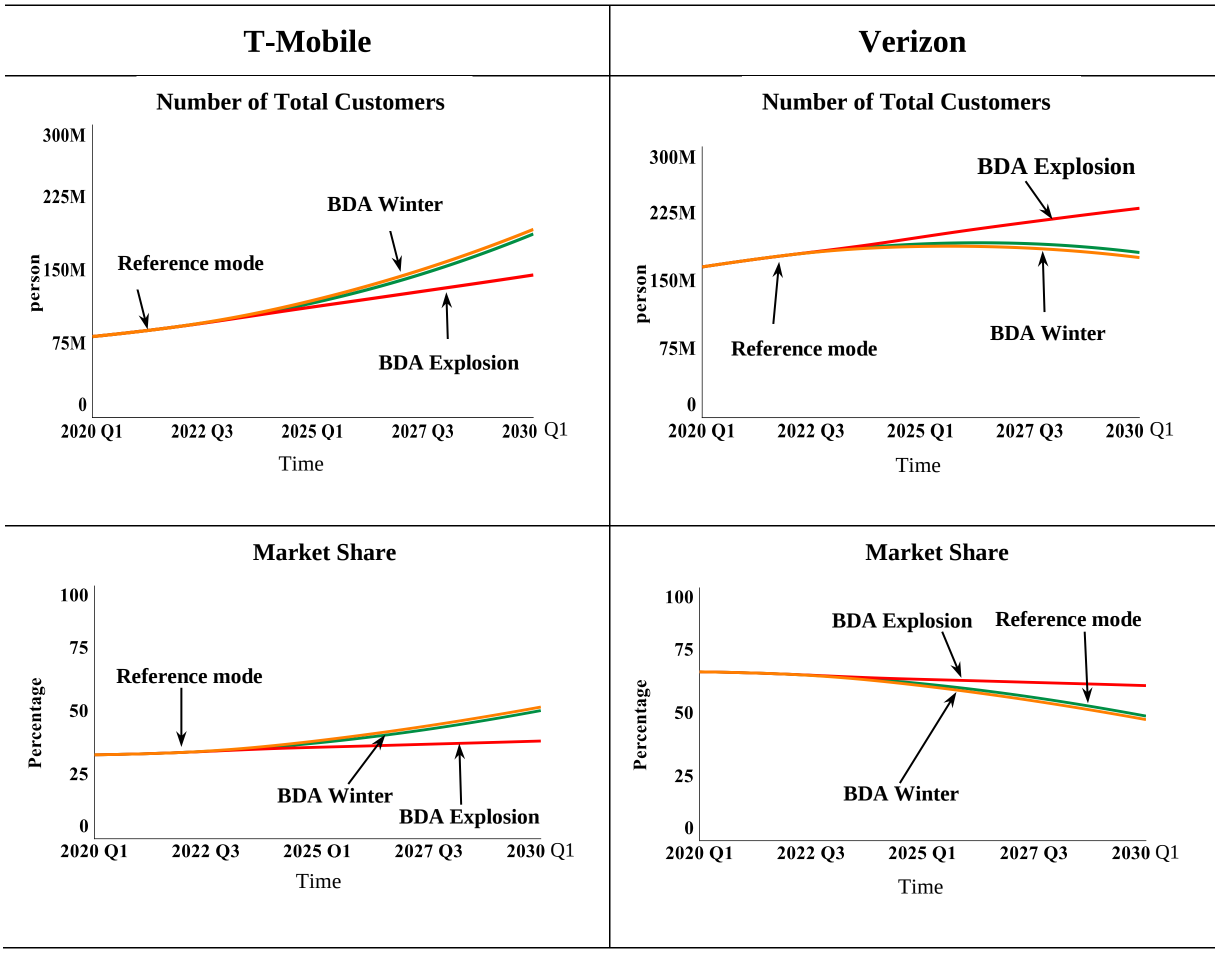


Figure 19. Number of Customers and Market Share Under the Three BDA Scenarios

This is in line with my expectation such that big firms (e.g., Verizon) produce and collect more customer data than small firms (e.g., T-Mobile). As data volume has a negative effect on the data storage cost and this negative effect gets stronger when data volume is bigger, large firms will achieve a bigger economy of scale by saving costs with additional data collected from customers. This competitive advantage of large firms is reinforced when the data storage cost becomes smaller. Further, the lower data acquisition cost means that firms are able to collect more data from customers. As such, in addition to the higher amount of data acquired per customer per month, the difference in the size of the firms' customer bases would become bigger between large and small firms. Consequently, the benefits from big data and BDA (e.g., through the firm's knowledge of customers) for large firms will outweigh the costs, leading to higher firm performance such as market share, firm revenue, and profit. For small firms, although the relative benefits of big data and BDA become smaller, leading to lower market share and firm revenue, they might have benefits from lower costs, that might lead to a slightly higher net profit.

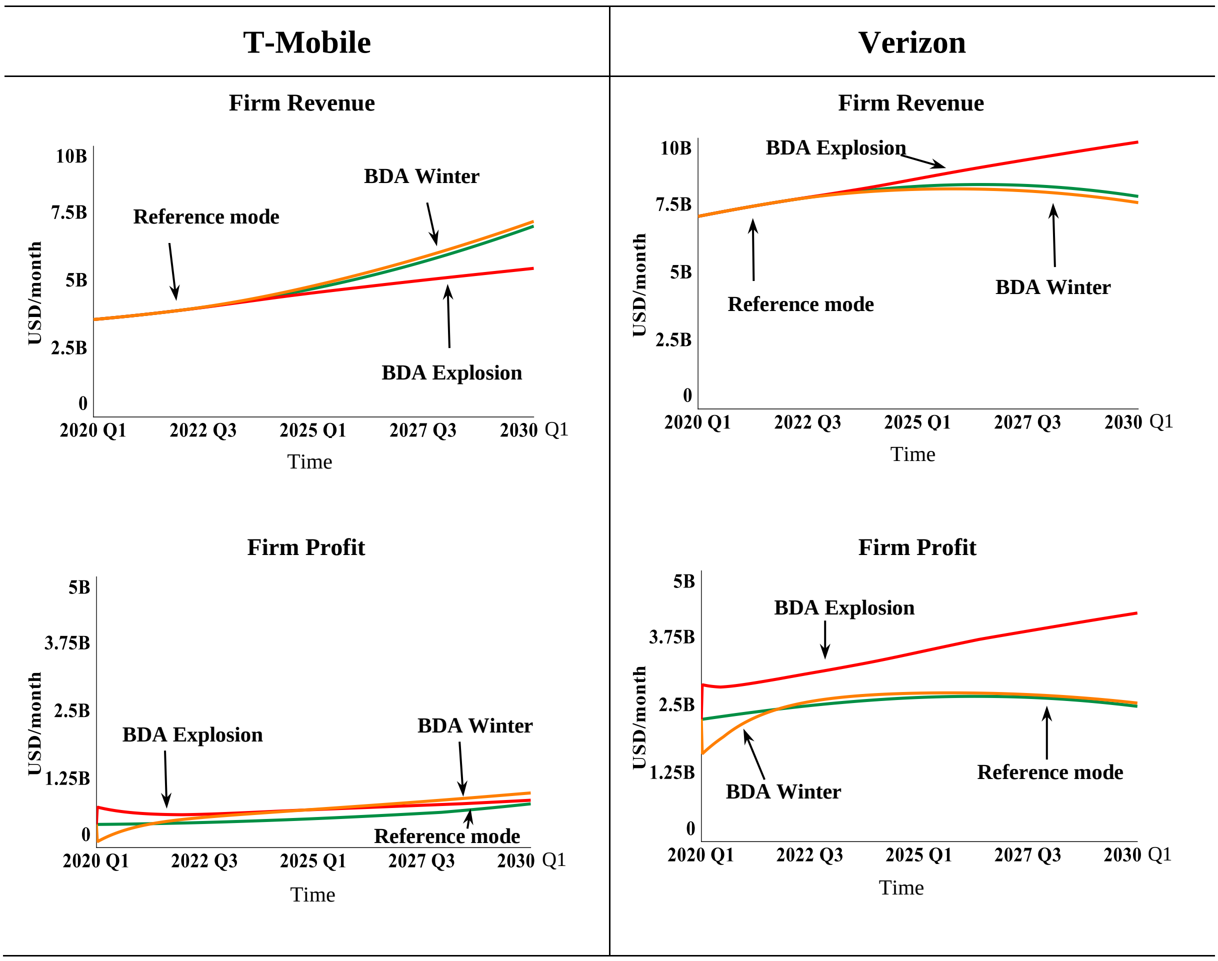


Figure 20. Firm Revenue and Profit Under the Three BDA Scenarios

In contrast, when the acquisition become more expensive, in addition to smaller data acquisition from new customers, the difference in the size of the firms' customer bases would become smaller between large and small firms. In addition, the higher data storage cost will reduce the competitive advantage of large firms in saving costs from additional collected data. Consequently, the costs of big data and BDA would outstrip the benefits, leading to lower firm performance for large firms. As small firms have smaller data, they are less affected by this negative effect and therefore getting stronger in the market. In my case, when T-Mobile gains more than 50% of market share, they become the larger firm, meaning that Verizon starts realizing the benefit of the smaller firm, leading to a slight increase in the profit.

Chapter 8: Policy Options Analysis

8.1 Overview of the Policy Formulation

The results from previous chapters about model calibration, sensitivity tests, and scenario analysis provide us with important insights into how BDA investments affect the dynamics of different firm outcomes including the number of total customers, firm revenue, and net profit. As shown in Figure 21, when there are no policy intervention and changes in my model assumptions (as suggested in my scenario analysis), the market develops in favor of T-Mobile, while Verizon is gradually losing its market share and firm revenue and will eventually lose its role as the bigger firm in the market. Hence, in this chapter, for each of these two firms, I will suggest different policies, focusing on BDA investments, to help them enhance their performance in this duopoly market.

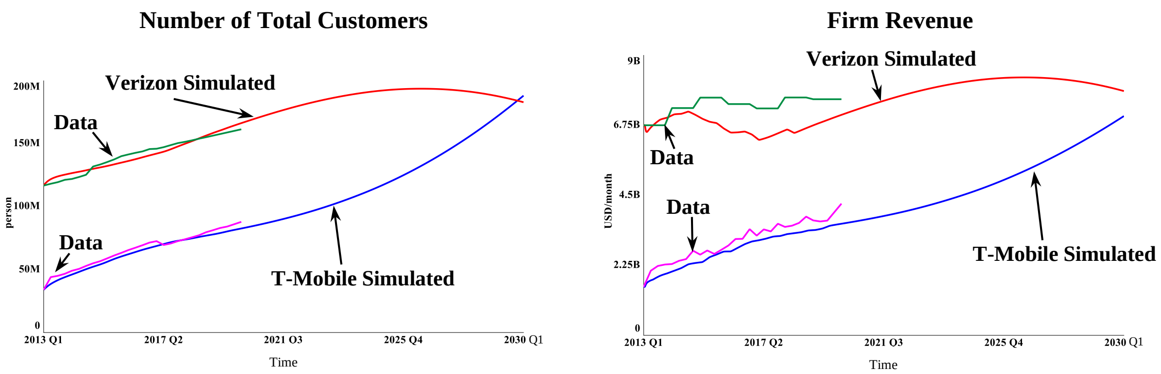


Figure 21. Market Share and Firm Revenue with No Policy Intervention

Table 9 outlines the settings of the four policy options proposed. As the market contains two firms, I assume that one firm will have to make the first move, and the other firm will decide whether to react or not. As shown in Figure 21, T-Mobile seems to be better off if they wait for the first move from Verizon. This is what I call “No Policy Intervention”, in which no firms make any change in their BDA-related investments. Verizon, who is experiencing decreasing trends in market share and firm revenue, cannot remain unchanged. Instead, they should make the first move to improve their customer acquisition. As this thesis focuses on the benefits of BDA, the proposed policies are based on three BDA-related variables including Fraction of Investment in BDA, Fraction of Investment in Data Acquisition, and Utilization of Investment in Extra Data Acquisition, while all other factors are held constant. The first move of Verizon, called “Verizon First Move”, is a policy in which this firm doubles its investment in BDA and in data acquisition, and increases the utilization of data acquisition investment by a factor of three such that the firm will over-utilize its investment in extra data acquisition to collect more data at a cost of lower quality. Then, I suggest two alternative reaction policies for T-Mobile to respond to the extra investments from Verizon. The first reaction policy, called “T-Mobile Reaction 1”, implies that T-Mobile follows precisely what Verizon has done in their first move. In the second reaction policy, called “T-Mobile Reaction 2”, implies a more aggressive investment policy for T-Mobile such that the fraction of investments in BDA and data acquisition will be increased by 400%. I analyze these policies and report the results in the next part.

Investment Policies	Variable	Change
No Policy Intervention	- Fraction of Investment in BDA	0% change
	- Fraction of Investment in Data Acquisition	0% change
	- Utilization of Investment in Extra Data Acquisition	0% change
Verizon First Move	- Fraction of Investment in BDA	100% growth
	- Fraction of Investment in Data Acquisition	100% growth
	- Utilization of Investment in Extra Data Acquisition	200% growth
T-Mobile Reaction 1	- Fraction of Investment in BDA	100% growth
	- Fraction of Investment in Data Acquisition	100% growth
	- Utilization of Investment in Extra Data Acquisition	200% growth
T-Mobile Reaction 2	- Fraction of Investment in BDA	400% growth
	- Fraction of Investment in Data Acquisition	400% growth
	- Utilization of Investment in Extra Data Acquisition	200% growth

Table 9. Policy Settings

8.2 Results of Policy Analysis

8.2.1 No policy intervention

As mentioned above, when no policy is implemented, T-Mobile is better off due to a higher product attractiveness that will help this firm to eventually win more than 50% of the total market (see Figure 21). The results of this option will be used as the benchmark to compare the three other policy options.

8.2.2 Verizon first move

My simulation results show that an increase in the amount of investment in BDA and data acquisition and utilization of data acquisition investment leads to a sharp increase of in the number of total customers and market share for Verizon (67% and 62% growth respectively compared to no policy) (see Figure 22 and Table 10). In contrast, this policy leads to a sharp decrease in the number of total customers and market share for T-Mobile (59% and 61% decline compared to no policy) (see Figure 22 and Table 10).

In addition, as shown in Figure 23, this policy leads to an increase in the total revenue and profit of Verizon (66% and 61% growth respectively), while it is a decrease for firm revenue and profit of T-Mobile (59% and 69% decline respectively) (see Figure 23 and Table 10).

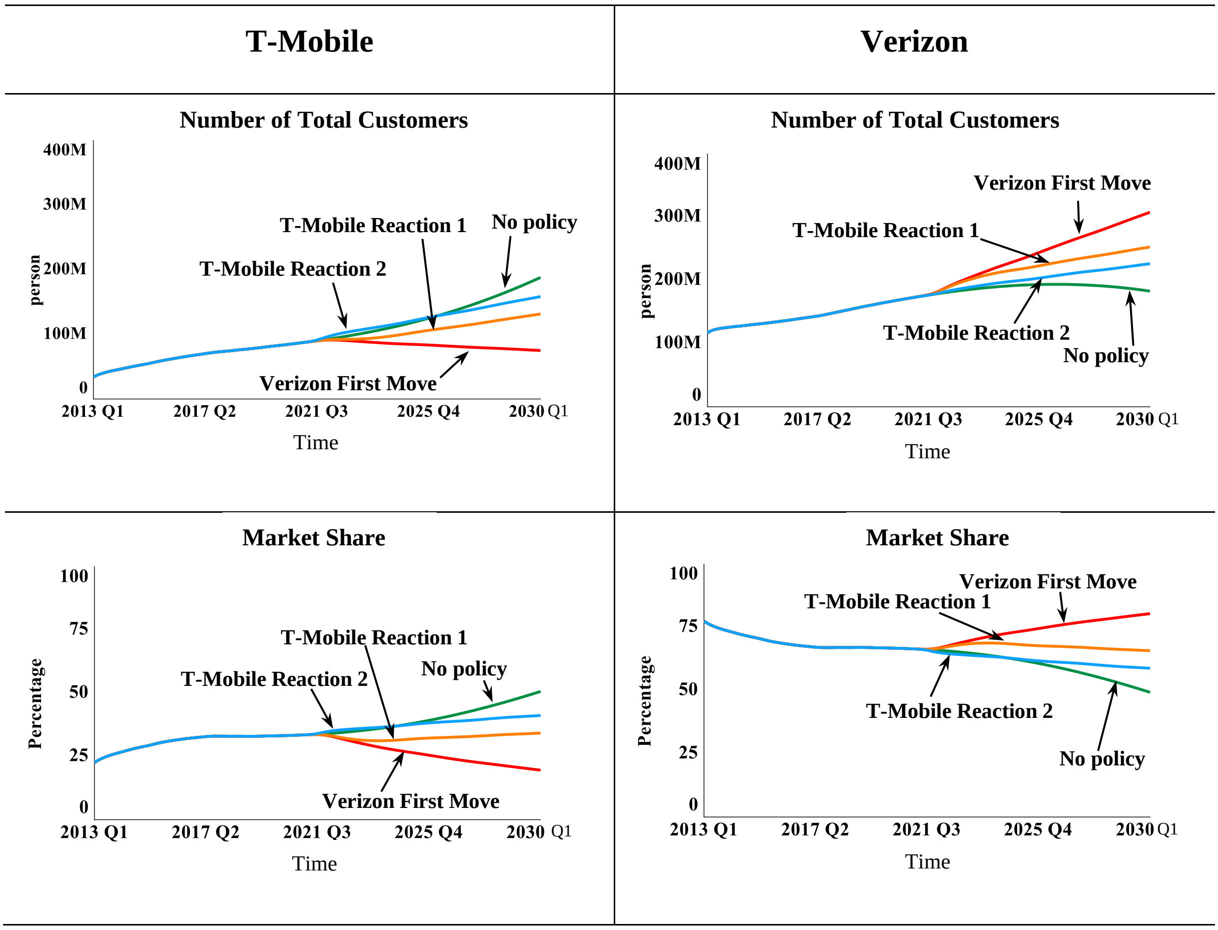


Figure 22. Number of Customers and Market Share Under the Three Policy Options

8.2.3 T-Mobile reaction 1

As Verizon would quickly dominate the market if this firm makes the first move as above, it is assumed that T-Mobile would be able to anticipate this and perform an immediate reaction to defend its market share. In this policy, I suggest that T-Mobile follows Verizon to equally increase the fractions of investments in BDA and data acquisition, in addition to an equal increase in the utilization of data acquisition investment. As shown in Figure 22 and Table 10, while still losing customers and market share, T-Mobile performs better than when there is no reaction (74% and 74% growth respectively compared to no reaction from T-Mobile). Similarly, while the total number of customers and market share of Verizon still increase compared to no policy, this reaction from T-Mobile significantly reduces this change (18% decline in both number of customers and market share compared to no reaction from T-Mobile).

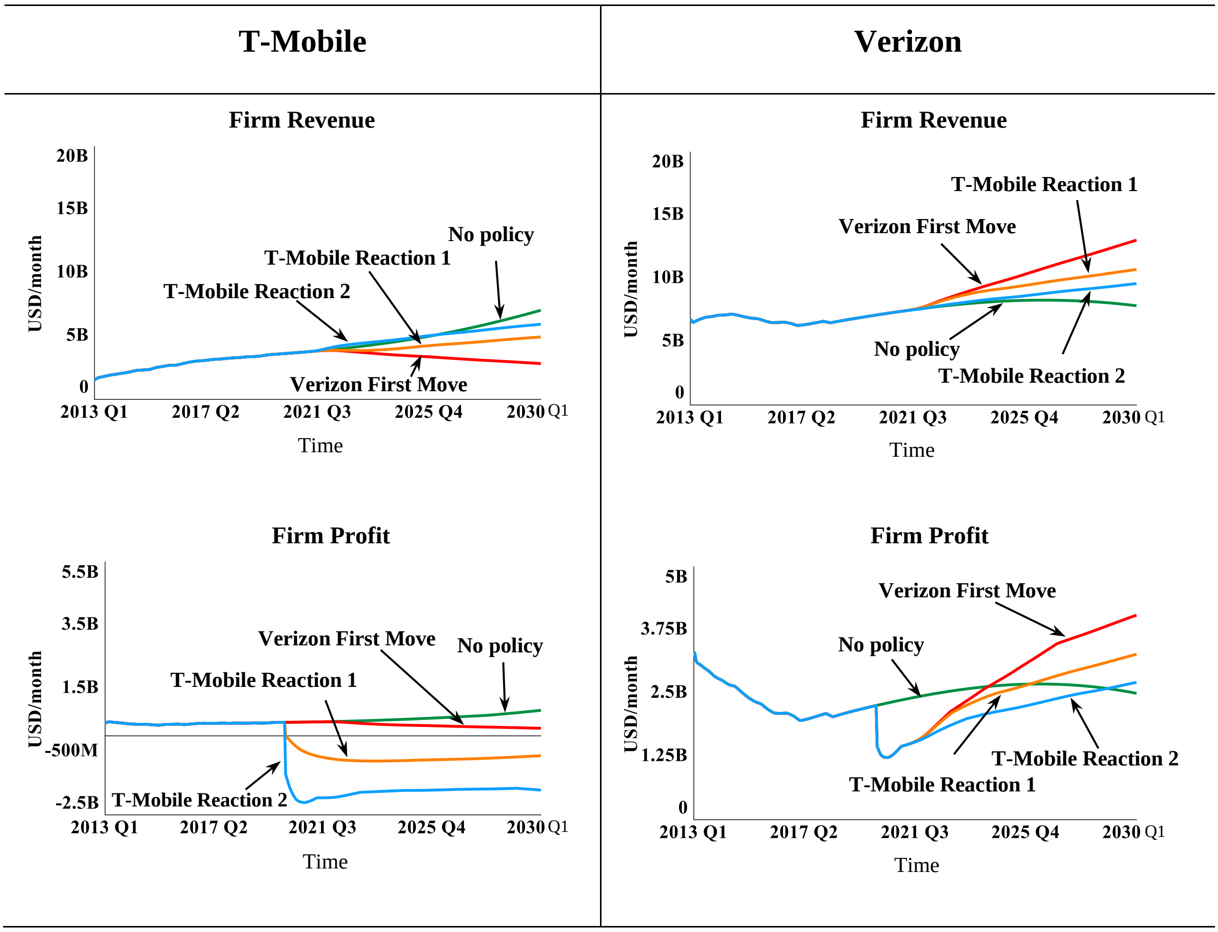


Figure 23. Firm Revenue and Profit Under the Three Policy Options

Furthermore, as shown in Figure 23 and Table 10, T-Mobile's revenue is still lower than when there is no policy (29% lower) but is better than no reaction (73% higher). Similarly, Verizon's revenue is higher than when there is no policy (36% higher) but lower than when there is no reaction from T-Mobile (18% lower). Nevertheless, this reaction from T-Mobile requires significant expenditure on BDA and data acquisition activities, leading to a significant decrease in the firm profit. Consequently, T-Mobile's net profit is lower than in both no policy and no reaction situations (177% decline compared to no policy, see Table 10). In contrast, Verizon's net profit is lower than when there is no reaction (20% decline) but higher than no policy due to higher revenue (30% growth).

8.2.4 T-Mobile reaction 2

In this more aggressive reaction policy, I assume that T-Mobile decides to sacrifice more profit for market share. More particularly, I suggest that T-Mobile increases the fractions of investments in BDA and data acquisition significantly higher than Verizon does, in addition to an equal increase in the utilization of data acquisition investment (see Table 9). As a result, although T-Mobile still lose customers and market share compared to no policy (17% and 20% decline respectively), this firm performs much better than when there is no reaction (104% and 104% growth respectively compared to no reaction from T-Mobile). Similarly, while the total number of customers and market share of Verizon still increase compared to no policy (25% and 21% growth respectively), this more aggressive reaction from T-Mobile further reduces the change (25% decline in number of customers and 26% decline in market share compared to no reaction from T-Mobile).

Policy Results	T-Mobile			Verizon		
Verizon First Move	2030 Q1	No policy	Change (%)	2030 Q1	No policy	Change (%)
Number of Customers (million people)	76.3	188	**-59.41**	306	183	**67.21**
Market share (%)	19.90	50.70	**-60.75**	80.10	49.30	**62.47**
Net Revenue (billion $/month)	2.88	7.05	**-59.15**	13.00	7.85	**65.61**
Net Profit (billion $/month)	0.25	0.81	**-69.14**	4.03	2.50	**61.20**
T-Mobile Reaction 1	2030 Q1	No policy	Change (%)	2030 Q1	No policy	Change (%)
Number of Customers (million people)	133	188	**-29.26**	251	183	**37.16**
Market share (%)	34.60	50.70	**-31.76**	65.40	49.30	**32.66**
Net Revenue (billion $/month)	4.99	7.05	**-29.22**	10.70	7.85	**36.31**

Net Profit (billion $/month)	-0.62	0.81	**-176.54**	3.24	2.50	**29.60**

T-Mobile Reaction 2	2030 Q1	No policy	Change (%)	2030 Q1	No policy	Change (%)
Number of Customers (million people)	156	188	**-17.02**	229	183	**25.14**
Market share (%)	40.50	50.70	**-20.12**	59.50	49.30	**20.69**
Net Revenue (billion $/month)	5.85	7.05	**-17.02**	9.70	7.85	**23.57**
Net Profit (billion $/month)	-1.94	0.81	**-339.51**	2.76	2.50	**10.40**

Table 10. Results of Policy Implementation in the First Quarter of 2030

In addition, as shown in Figure 23 and Table 10, T-Mobile's revenue is still lower than when there is no policy (17% lower) but is better than reaction 1 (17% higher). Similarly, Verizon's revenue is higher than when there is no policy (24% higher) but lower than T-Mobile's reaction 1 (9% lower). Nevertheless, this reaction from T-Mobile requires more expenditure on BDA and data acquisition activities, leading to further sacrifice of firm profit. Consequently, T-Mobile's net profit is lower than all other policy options (340% decline compared to no policy, see Table 10). In contrast, Verizon's net profit is lower than T-Mobile' reaction 1 (15% decline) but still slightly higher than no policy due to higher revenue (10% growth).

8.3 Policy Implementation Under Different Scenarios

In this part, I simulate the model to test the above policies when the situation is changed as mentioned in Chapter 7. More specifically, I rerun the above policies to test its interaction with different scenarios, namely when the future is in favor of BDA activities (BDA Explosion scenario) and when it develops against the development of BDA activities (BDA Winter scenario).

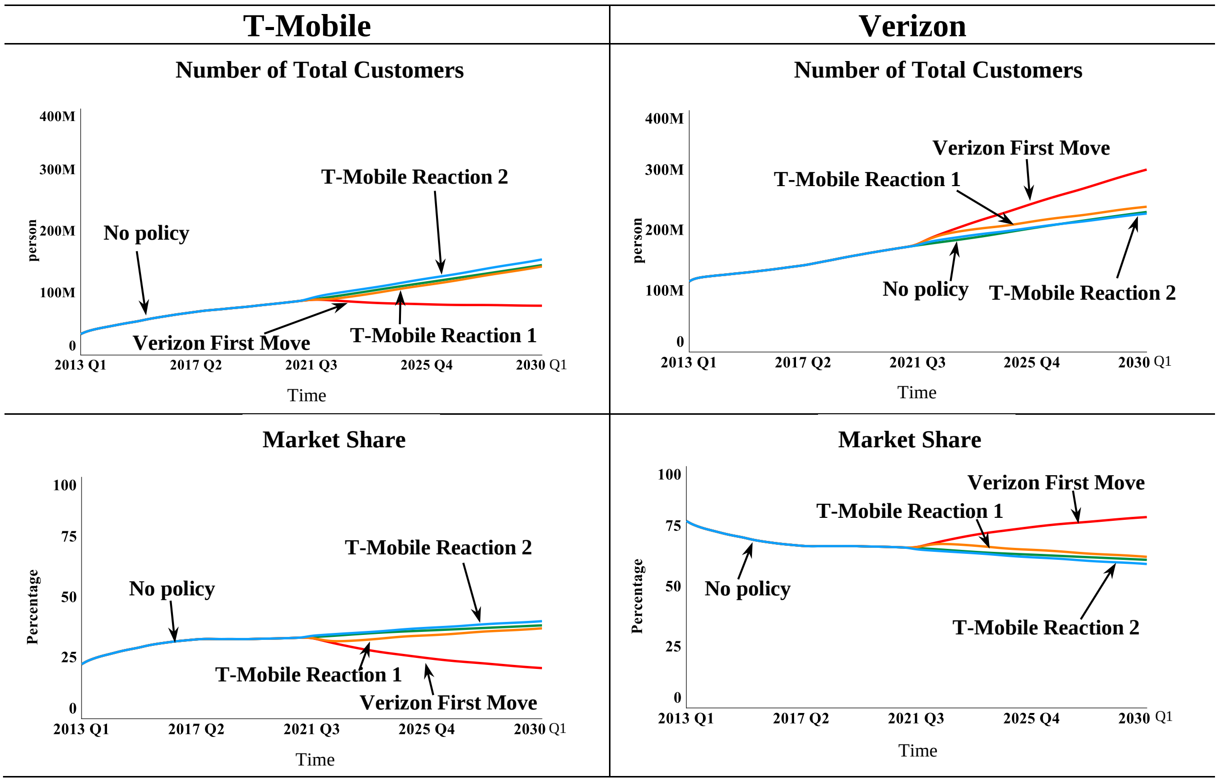


Figure 24. Number of Customers and Market Share Under the Three Policy Options and BDA Explosion Scenario

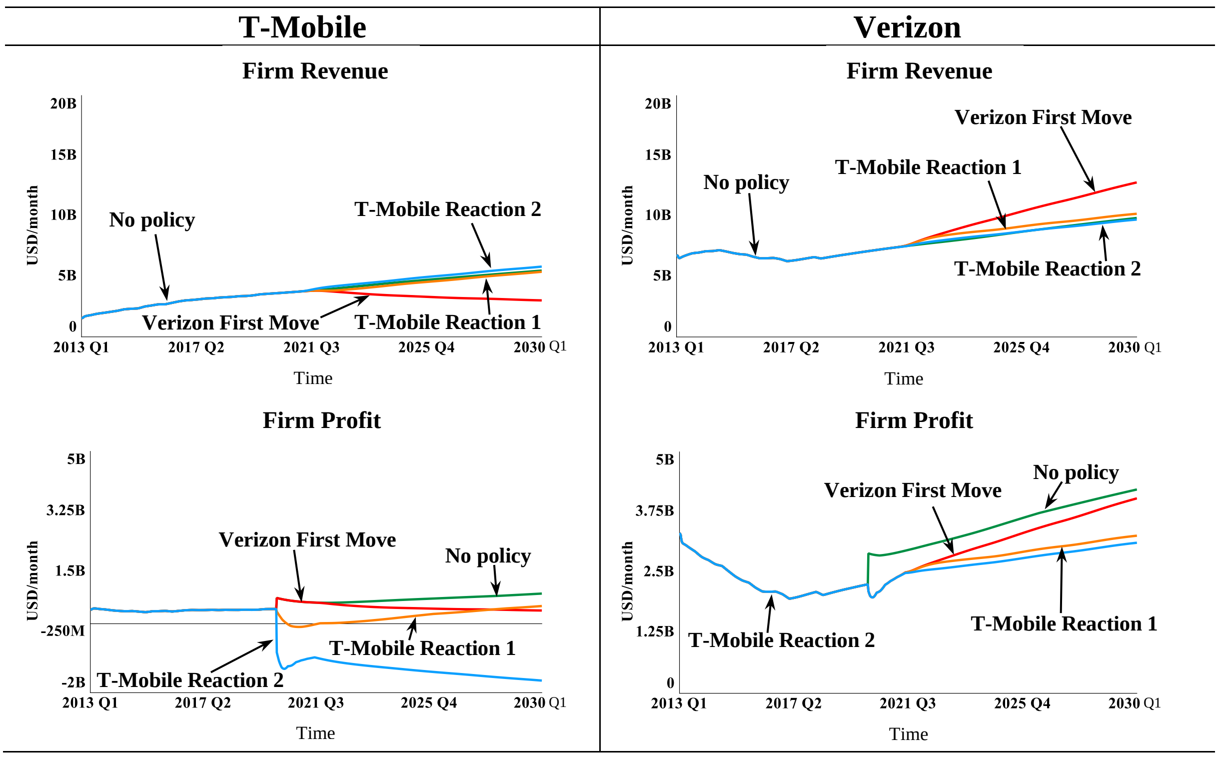


Figure 25. Firm Revenue and Profit Under the Three Policy Options and BDA Explosion Scenario

As seen in Figures 24, 25, 26, and 27, the model produces similar result patterns, especially between the BDA Winter scenario and the reference mode (no change in data storage and acquisition costs and utilization of data acquisition investment). In the BDA Explosion scenario, my proposed policy for Verizon, however, is slightly less effective. This is in line with my expectation such that in the BDA explosion scenario, as customers generate more data for the firms and the data storage and acquisition costs are lower, BDA investments become more productive, making the optimal amount of investments become lower for Verizon. As shown in Figure 24, while the policy Verizon First Move is still effective in gaining customers and increasing revenue, it takes longer time for Verizon to regain the similar level of net profit compared to when there is no policy intervention. In contrast, the more aggressive reaction of T-Mobile becomes more effective such that T-Mobile obtains a slightly higher market share than when there is no policy. This is also supported by the higher productivity of BDA investments.

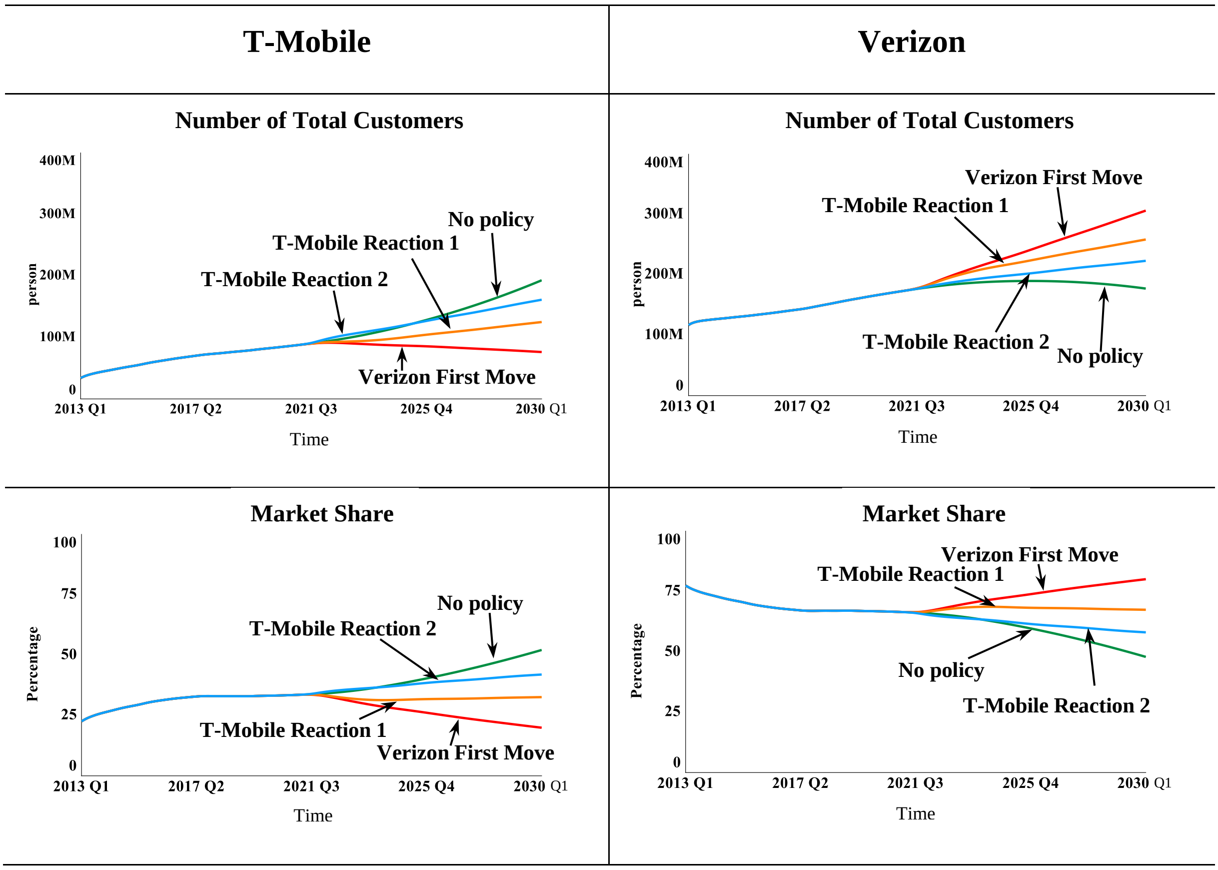


Figure 26. Number of Customers and Market Share Under the Three Policy Options and BDA Winter Scenario

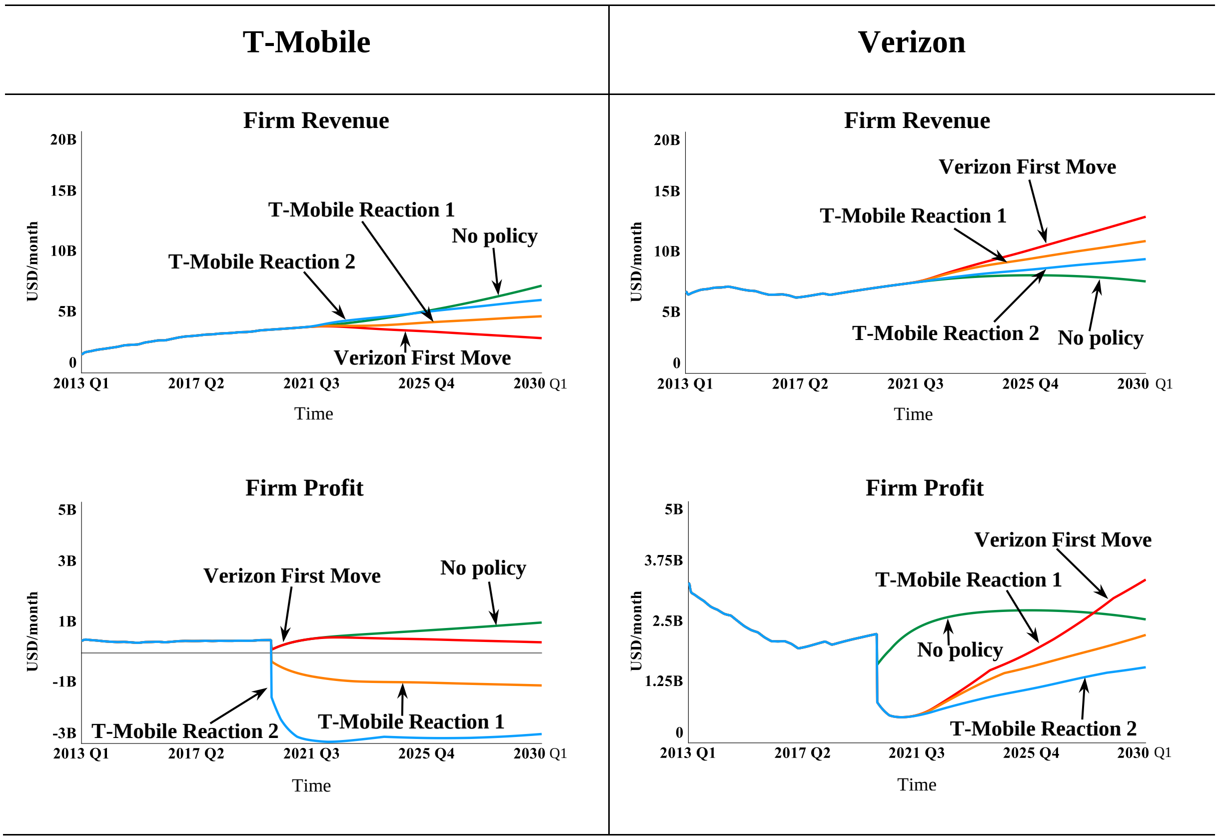


Figure 27. Firm Revenue and Profit Under the Three Policy Options and BDA Winter Scenario

8.4 Policy Discussion

Advanced analytics using big data plays a crucial role in customer acquisition and therefore driving firm revenue and profit. Nevertheless, BDA investment does not always produce positive value to the firm. On the one hand, big analytics such as machine learning or deep learning require a reasonably large amount of data such that small data would make analytics less productive. On the other hand, too much data would be less helpful as the firm would reach to the point where additional customer data no longer increases the productivity of the BDA activities (Hagiu & Wright, 2020), leading to a diminishing return on investment in BDA as mentioned in Chapter 4. In other words, investing too much in big data acquisition would lead to too much data such that the storage costs would outweigh the benefits of the additional information, while investing too little in big data acquisition would make it less productive.

Further, as big data provides no value if there is no analytics, an investment in data acquisition would be more beneficial when a similar investment is made to enhance BDA activities. The results of my policy analysis reveal that Verizon, by increasing its investments in BDA and data acquisition, could increase its market share, total revenue, and net profit significantly. In addition, by increasing the utilization of investment in data acquisition, Verizon can increase data volume more quickly at the cost of lower data accuracy (as well as consistency and timeliness). It is of note that trading too much data quality for data volume might be detrimental as data quality is also an important determinant of the productivity of BDA investment.

The reaction from T-Mobile, however, is less effective. To offset the competition from Verizon, T-Mobile would need to make a bigger increase in its investments in BDA and data acquisition. One major reason is that Verizon owns a bigger customer database. In 2020, Verizon has more than 150 million subscribers, while T-Mobile only has 86 million subscribers. As data storage and acquisition cost reduces when data volume increases, the difference of about 60 million customers provides Verizon with a cost advantage that helps this firm leverage its investments in big data more quickly. This economy of scale becomes particularly more important when the business environment is developing in favor of BDA activities (as in my BDA Explosion scenario, see Chapter 7). In this scenario, as BDA investment is more productive, the optimal amount of investments in big data seems to be lower for Verizon and the reaction from T-Mobile is also more effective.

In fact, emerging evidence shows that firms are increasing their investments in big data and BDA (e.g., Columbus, 2016). While it is admitted that increasing the BDA investment by 100% appears to be a critical decision for Verizon and T-Mobile, we can compute the actual increase in the investment amount to see that it is roughly 0.06*91 = 5.46 billion dollars per year for Verizon, and 0.06*48 = 2.88 billon dollars per year for T-Mobile. This could be translated to a big investment of about $20 billon for 4 years, which is comparable to a total of $17.8 billon that Verizon has invested in the expansion of 4G LTE network in the U.S., which only lasted from 2015 to 2019 when the 5G service has been launched with a similar amount of investment (K, 2016; Kinney, 2020). As investing in BDA might include building up a BDA platform such that, for example, data can be transferred between different departments or locations, in addition to hiring employees with BDA talent, the suggested amount of investments in my policies is high but reasonably acceptable.

A combination of policy implementation and different scenarios shows that the proposed policies are robust to the change of different environmental factors. Furthermore, the results suggest that big data can put small firms at a disadvantage. For example, in order to offset the competition from Verizon (e.g., increasing investments in BDA), T-Mobile would have to make a bigger increase in its BDA investments, meaning that the firm has to sacrifice its profit for market share. This is in line with recent studies showing that large firms with large customer bases can exploit their economies of scale in BDA investments to flourish, while small firms with small data are struggling with the big costs of BDA investments (e.g., Mihet & Philippon, 2019). One potential policy, which is out of the scope of this thesis, to solve this inequality among firms is that the local government might help small firms generate more data or access big data at a low cost (e.g., Farboodi, 2018). For example, in 2016, in an attempt to reduce the ratio of business failures, the Seoul city government has launched a service that allows small businesses to access hundreds of billion data points to do market analysis and other advanced analytics on customer behaviors (Seoul Urban Solutions Agency, 2016).

Chapter 9: Conclusion, Implications, and Limitations

9.1 Conclusion

As stated by Farboodi (2018), many firms are heavily investing in big data and BDA nowadays in hopes that they can magically lift up the productivity of their employees, give them insights to make accurate predictions about customers' preferences and purchase patterns, or reduce costs and increase firm profitability, etc. Unfortunately, more than half of these firms were not able to achieve their goals, and nearly half of them did not experience any benefits of BDA investments at all (Côrte-Real et al., 2019). Big data, just like any other strategic resources of the firms, comes with both benefits and costs. Importantly, managers often disregard the continuous feedback processes between BDA investments and its business values, and thus are not able to predict when a massive amount of data becomes an asset and when it becomes a cost (Hagiu & Wright, 2020).

The results of this thesis reveal that BDA investments lead to an increase in firms' knowledge of customers, which in turn, will have a positive impact on marketing effectiveness, people' willingness to become a customer, and customer retention. As this process is driven by several reinforcing loops (e.g., more investments, more revenues and more revenues, more investments), firms have a tendency to overinvest in BDA. My model shows that, the value of BDA investments, however, is limited by at least two major balancing loops. First, the more knowledge the firm has about its customers, the more difficult it is to increase it. Thus, at some point, extra investment in BDA would be very unproductive and extra data acquisition would only increase storage cost without producing any benefit. Second, even if firms can gain more knowledge about customers, applying it in other activities would become increasingly difficult at some point. Specifically, if the quality of the marketing activities is already high, it would be very difficult to increase it further, even with more customer insights. The combination of different negative and positive feedback loops included in my model reflects part of the complexity inherently associated with the dynamic influence of big data and BDA on firm performance.

Another important result of my model is that, as expected, big data seems to favor large firms over the smaller ones. The simulation results reveal that if the use of BDA and big data is getting more and more popular among the firms leading to lower cost of data storage and data acquisition, in addition to more data generated by customers, large firms would quickly get more benefits from their BDA investments, resulting in a steady growth rate of their market share. This winner-take-all problem comes from the fact that large firms produce more data than small firms and therefore, due to economies of scale, have a competitive advantage when investing in data acquisition and BDA. The results of my policy analysis suggest that, by increasing their investments in BDA and data acquisition, large firms would increase their customer acquisition. These firms would experience a higher cost at the beginning, but the extra revenues will eventually outstrip the extra expenses.

It is more difficult, however, for small firms to compete using BDA. My results reveal that, with lower data volume to start with, small firms need to invest more heavily than large firms to offset the competition. While a significant increase in investments in BDA and data acquisition might help small firms defend their market share, this means they need to sacrifice a significant part of their profits which might take them years to regain. One can also argue that a large number of customers might be more beneficial in the long term compared to some loss on profit in the short term. Amazon and its low-priced Kindles are an example of how gaining more customers is more important long-term than short-term profit (i.e., people buy more books and accessories after buying a Kindle) (Clay, 2012). Nevertheless, it seems that the costs of just not losing the game (market share) for small firms might be too high in this big data competition. Some recent research has suggested that governments might intervene to resolve this issue of inequality such that small and medium businesses would be granted access to big data at a lower cost (Begenau et al., 2018). It is unclear, though, that how this policy is useful for the whole industry, as it might discourage every firm from taking the lead in BDA investments. This is, however, out of the scope of this thesis.

9.2 Potential Implications

The results of this thesis provide managers with several potential implications. First, large firms should take advantage of their economies of scale in BDA investments. It is of note that too much investment would be harmful, as the expansion of business value of BDA is limited by several diminishing returns of investment in data acquisition and direct marketing as mentioned above. Small firms are at a disadvantage when competing against large firms using big data and BDA. Note that there are other (better) ways of competition, which are however not discussed in this paper.

Second, as advanced analytics such as machine learning and artificial intelligence often require a large amount of data, many firms are investing to increase data volume at a cost of data quality. This is an interesting trade-off as it can lead to a quick increase in data volume, which might return a positive impact in customer acquisition and firm revenue. Nevertheless, the results of my simulation show that trading too much data quality for data volume might decrease the quality of marketing activities, leading to lower marketing effectiveness and consequently lower number of new customers. As I do not have any real data about the data quality at the two studied firms, I leave it for future research to explore, which I will discuss in the next part.

9.3 Limitations and Future Research

My study contains several limitations. First, for simplicity purposes, I only tested two firms with different market share in the total market. In addition, I assume that their revenues only come from subscription and activation fees and exclude all other products and services. Future research might consider including more firms with similar market share but different expenditure structures (e.g., marketing expenditure) to explore the impact of BDA investments when no one has cost advantages. A full set of telecoms products and services should also be considered to test the robustness of my findings.

Second, because of time constraint and data unavailability, my model does not include the dynamics in the firms' employment. In fact, many firms make big investments in recruiting talents in data science and data analysis, in an effort to take full advantage of their big data. As such, the costs of recruitment and staff training might play a role in evaluating the impact of big data and BDA investments. Another relevant aspect is that BDA investments might result in more tasks being automated, leading to higher working productivity and lower need for employees.

Finally, in this study, I assume that investments are fractions of total revenue which remain over time. While fixing these fractions help clarify the advantage of large firms over small ones (e.g., more revenues, more investments), future research might explore different feedback processes involved between these two variables. For example, one might argue that an increase in firm revenue might lead to a decrease in investment as the return on investment is diminishing over time. In contrast, one might argue that investment should be made dependent on the potential of the market. For example, if there are still many prospective customers to target, firms should keep investing more on BDA and direct marketing. Further research should therefore explore the impact of these different investment policies that might be implemented differently in different firms.

REFERENCES

Ambler, T., & Roberts, J. H. (2008). Assessing marketing performance: don't settle for a silver metric. *Journal of Marketing Management, 24*(7-8), 733-750. doi:10.1362/026725708X345498

Antons, D., & Breidbach, C. F. (2017). Big Data, Big Insights? Advancing Service Innovation and Design With Machine Learning. *Journal of Service Research, 21*(1), 17-39. doi:10.1177/1094670517738373

Aradhya, P. (2020). Actioning Individual Customer Context With Artificial Intelligence. Retrieved from https://www.forbes.com/sites/forbesbusinesscouncil/2020/04/01/actioning-individual-customer-context-with-artificial-intelligence/#533314fa4ea5

Aydiner, A. S., Tatoglu, E., Bayraktar, E., Zaim, S., & Delen, D. (2019). Business analytics and firm performance: The mediating role of business process performance. *Journal of Business Research, 96*, 228-237. doi:https://doi.org/10.1016/j.jbusres.2018.11.028

Azeem Qureshi, M. (2007). System dynamics modelling of firm value. *Journal of Modelling in Management, 2*(1), 24-39. doi:10.1108/17465660710733031

Barlas, Y. (1996). Formal aspects of model validity and validation in system dynamics. *System Dynamics Review, 12*(3), 183-210. doi:10.1002/(sici)1099-1727(199623)12:3<183::Aid-sdr103>3.0.Co;2-4

Bass, F. M. (1969). A New Product Growth For Model Consumer Durables. *Management Sience, 15*(5), 215-227.

Bass, F. M., Krishnamoorthy, A., Prasad, A., & Sethi, S. P. (2005). Generic and Brand Advertising Strategies in a Dynamic Duopoly. *Marketing Science, 24*(4), 525-648. doi:https://doi.org/10.1287/mksc.1050.0119

Becker, J. U., Greve, G., & Albers, S. (2009). The impact of technological and organizational implementation of CRM on customer acquisition, maintenance, and retention. *International Journal of Research in Marketing, 26*(3), 207-215. doi:https://doi.org/10.1016/j.ijresmar.2009.03.006

Begenau, J., Farboodi, M., & Veldkamp, L. (2018). Big data in finance and the growth of large firms. *Journal of Monetary Economics, 97*, 71-87. doi:https://doi.org/10.1016/j.jmoneco.2018.05.013

Belyh, A. (2019). Big Data and New Product Development. Retrieved from https://www.cleverism.com/big-data-new-product-development/

Boothby, E. J., Clark, M. S., & Bargh, J. A. (2014). Shared Experiences Are Amplified. *Psychological Science, 25*(12), 2209-2216.

Bradlow, E. T., Gangwar, M., Kopalle, P., & Voleti, S. (2017). The Role of Big Data and Predictive Analytics in Retailing. *Journal of Retailing, 93*(1), 79-95. doi:https://doi.org/10.1016/j.jretai.2016.12.004

Bradner, J. W. (2016). The Digital Age: Opportunities for Startups and Scale-ups. Retrieved from https://www.genglobal.org/digital-age-opportunities-startups-and-scale-ups

Bughin, J. (2016a). Big data, Big bang? *Journal of Big Data, 3*(1), 2. doi:10.1186/s40537-015-0014-3

Bughin, J. (2016b). Reaping the benefits of big data in telecom. *Journal of Big Data, 3*(1), 14. doi:10.1186/s40537-016-0048-1

Cacioppo, J. T., & Petty, R. E. (1979). Effects of message repetition and position on cognitive response, recall, and persuasion. *Journal of Personality and Social Psychology, 37*(1), 97-109. doi:10.1037/0022-3514.37.1.97

Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). Business Intelligence and Analytics: From Big Data to Big Impact. *MIS Quarterly, 36*(4), 1165-1188. doi:10.2307/41703503

Chung, T. S., Rust, R. T., & Wedel, M. (2009). My Mobile Music: An Adaptive Personalization System for Digital Audio Players. *Marketing Science, 28*(1), 52-68. doi:10.1287/mksc.1080.0371

Cialdini, R. B. (2007). Descriptive Social Norms as Underappreciated Sources of Social Control. *Psychometrika, 72*(2), 263-268.

Clay, K. (2012). Amazon Confirms It Makes No Profit On Kindles. Retrieved from https://www.forbes.com/sites/kellyclay/2012/10/12/amazon-confirms-it-makes-no-profit-on-kindles/#2b48430a6b43

Columbus, L. (2016). 51% Of Enterprises Intend To Invest More In Big Data. Retrieved from https://www.forbes.com/sites/louiscolumbus/2016/05/22/51-of-enterprises-intend-to-invest-more-in-big-data/#4531e561f61e
Côrte-Real, N., Ruivo, P., Oliveira, T., & Popovič, A. (2019). Unlocking the drivers of big data analytics value in firms. *Journal of Business Research, 97*, 160-173. doi:https://doi.org/10.1016/j.jbusres.2018.12.072
CTIA. (2020). Our Members. Retrieved from https://www.ctia.org/about-ctia/our-members
Davenport, T. H., Barth, P., & Bean, R. (2012). How 'Big Data' Is Different. *MIT Sloan Management Review, 54*, 22-24.
Davidsen, P. I., Sterman, J. D., & Richardson, G. P. (1990). A petroleum life cycle model for the United States with endogenous technology, exploration, recovery, and demand. *System Dynamics Review, 6*(1), 66-93. doi:10.1002/sdr.4260060105
Deutskens, E., de Ruyter, K., Wetzels, M., & Oosterveld, P. (2004). Response Rate and Response Quality of Internet-Based Surveys: An Experimental Study. *Marketing Letters, 15*(1), 21-36. doi:10.1023/B:MARK.0000021968.86465.00
Dibb, S., Rushmer, A., & Stern, P. (2001). New Survey Medium: Collecting Marketing Data with E-Mail and the World Wide Web. *Journal of Targeting, Measurement and Analysis for Marketing, 10*(1), 17-25.
DNV GL Group. TL 9000 - Quality management in telecommunications.
Dong, J. Q., & Yang, C.-H. (2020). Business value of big data analytics: A systems-theoretic approach and empirical test. *Information & Management, 57*(1), 103124. doi:https://doi.org/10.1016/j.im.2018.11.001
Dong, X., Manchanda, P., & Chintagunta, P. K. (2009). Quantifying the Benefits of Individual-Level Targeting in the Presence of Firm Strategic Behavior. *Journal of Marketing Research, 46*(2), 207-221. doi:10.1509/jmkr.46.2.207
Duan, W., Gu, B., & Whinston, A. B. (2008). The dynamics of online word-of-mouth and product sales - An empirical investigation of the movie industry. *Journal of Retailing, 84*(2), 233-242.
Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big Data consumer analytics and the transformation of marketing. *Journal of Business Research, 69*(2), 897-904. doi:https://doi.org/10.1016/j.jbusres.2015.07.001
Farboodi, M. (2018). The Problem With Big Data. *MIT Sloan Management Review*. Retrieved from https://sloanreview.mit.edu/article/the-problem-with-big-data/
FierceWireless, & Statista. (2019). Wireless subscriptions market share by carrier in the U.S. from 1st quarter 2011 to 3rd quarter 2019. Retrieved from https://www.statista.com/statistics/199359/market-share-of-wireless-carriers-in-the-us-by-subscriptions/#:~:text=Wireless%20carrier%2Foperator%20subscriber%20share%20in%20the%20U.S.%202011%2D2019&text=AT%26T%20is%20the%20leading%20provider,operators%20in%20the%20United%20States.
Fong, N. M., Fang, Z., & Luo, X. (2015). Geo-Conquesting: Competitive Locational Targeting of Mobile Promotions. *Journal of Marketing Research, 52*(5), 726-735. doi:10.1509/jmr.14.0229
Forrester, J. W. (1958). Industrial Dynamics. A major breakthrough for decision makers. *Harvard Business Review, 36*(4), 37-66.
Forrester, J. W. (1964). *Modeling the dynamic processes of corporate growth.* Paper presented at the Proceedings of the IBM Scientific Computing Symposium on Simulation Models and Gaming.
Forrester, J. W., & Senge, P. M. (1980). Tests for building confidence in system dynamics models. *System dynamics, TIMS studies in management sciences, 14*, 209-228.
Ghasemaghaei, M., & Calic, G. (2019). Does big data enhance firm innovation competency? The mediating role of data-driven insights. *Journal of Business Research, 104*, 69-84. doi:https://doi.org/10.1016/j.jbusres.2019.07.006
Goddard, W. (2018). How Do Big Companies Collect Customer Data? Retrieved from https://itchronicles.com/big-data/how-do-big-companies-collect-customer-data/
Godes, D., & Mayzlin, D. (2004). Using Online Conversations to Study Word-of-Mouth Communication. *Marketing Science, 23*(4), 545-560.
Hagiu, A., & Wright, J. (2020). When data creates competitive advantage. *Harvard Business Review, 98*(1), 94-101.

Hallikainen, H., Savimäki, E., & Laukkanen, T. (2020). Fostering B2B sales with customer big data analytics. *Industrial Marketing Management, 86*, 90-98. doi:https://doi.org/10.1016/j.indmarman.2019.12.005
Hazen, B. T., Boone, C. A., Ezell, J. D., & Jones-Farmer, L. A. (2014). Data quality for data science, predictive analytics, and big data in supply chain management: An introduction to the problem and suggestions for research and applications. *International Journal of Production Economics, 154*, 72-80. doi:https://doi.org/10.1016/j.ijpe.2014.04.018
Hibbard, J. D., Brunel, F. F., Dant, R. P., & Iacobucci, D. (2001). Does Relationship Marketing Age Well? *Business Strategy Review, 12*(4), 29-35. doi:10.1111/1467-8616.00189
Homer, J., Hirsch, G., Minniti, M., & Pierson, M. (2004). Models for collaboration: how system dynamics helped a community organize cost-effective care for chronic illness. *System Dynamics Review, 20*(3), 199-222. doi:10.1002/sdr.295
Hovmand, P. S. (2014). Group model building and community-based system dynamics process. In *Community based system dynamics* (pp. 17-30): Springer.
Jeanjean, F. (2015). What causes the megabyte price drop in the mobile industry? *Economia e Politica Industriale, 42*(3), 277-296.
K, B. (2016). Verizon lowers telecom network Capex to $17.7 bn in 2016. Retrieved from https://www.telecomlead.com/4g-lte/verizon-lowers-telecom-network-capex-17-7-bn-2016-66805#:~:text=Verizon%20has%20made%20investment%20of,up%2011.5%20percent%20from%202014.
Khan, A., Qureshi, M. A., & Davidsen, P. I. (2020). How do oil prices and investments impact the dynamics of firm value? *System Dynamics Review*.
King, R. (2014). AT&T Uses Big Data to Improve Customer Experience. Retrieved from https://blogs.wsj.com/cio/2014/06/03/att-uses-big-data-to-improve-customer-experience/
Kinney, S. (2020). Verizon plans to invest $17 billion this year in 5G, LTE and fiber. Retrieved from https://www.rcrwireless.com/20200130/carriers/verizon-capex-5g-lte-fiber#:~:text=For%202020%2C%20Verizon%20said%20it,to%20full%2Dyear%202019.%E2%80%9D
Kotler, P., & Armstrong, G. (2017). *Principles of Marketing* (17 ed.). United Kingdom: Pearson Education Limited.
Kozinets, R. V., Valck, K. d., Wojnicki, A. C., & Wilner, S. J. S. (2010). Networked Narratives: Understanding Word-of-Mouth Marketing in Online Communities. *Journal of Marketing, 74*(2), 71-89.
Kumar, V., Bhagwat, Y., & Zhang, X. (2015). Regaining "Lost" Customers: The Predictive Power of First-Lifetime Behavior, the Reason for Defection, and the Nature of the Win-Back Offer. *Journal of Marketing, 79*(4), 34-55. doi:10.1509/jm.14.0107
Lam, S. K., Sleep, S., Hennig-Thurau, T., Sridhar, S., & Saboo, A. R. (2016). Leveraging Frontline Employees' Small Data and Firm-Level Big Data in Frontline Management: An Absorptive Capacity Perspective. *Journal of Service Research, 20*(1), 12-28. doi:10.1177/1094670516679271
Langer, E. J. (1975). The illusion of control. *Journal of Personality and Social Psychology, 32*(2), 311-328.
Leaser, D. (2014). The Need for Speed: Data-driven companies are winning the race! Retrieved from https://www.ibm.com/blogs/ibm-training/the-need-for-speed-data-driven-companies-are-winning-the-race/
Lee, M. Y., Lee, A. S., & Sohn, S. Y. (2013). Behavior scoring model for coalition loyalty programs by using summary variables of transaction data. *Expert Systems with Applications, 40*(5), 1564-1570. doi:https://doi.org/10.1016/j.eswa.2012.08.073
Leetaru, K. (2019). How Do We Define 'Big Data' And Just What Counts As A 'Big Data' Analysis? Retrieved from https://www.forbes.com/sites/kalevleetaru/2019/01/09/how-do-we-define-big-data-and-just-what-counts-as-a-big-data-analysis/#107ccb071b66
Liu, Y., Soroka, A., Han, L., Jian, J., & Tang, M. (2020). Cloud-based big data analytics for customer insight-driven design innovation in SMEs. *International Journal of Information Management, 51*, 102034. doi:https://doi.org/10.1016/j.ijinfomgt.2019.11.002

MacNaught, S. (2014). Tecmark survey finds average user picks up their smartphone 221 times a day. Retrieved from https://www.tecmark.co.uk/blog/smartphone-usage-data-uk-2014
Maier, F. H. (1998). New product diffusion models in innovation management—a system dynamics perspective. *System Dynamics Review, 14*(4), 285-308. doi:10.1002/(sici)1099-1727(199824)14:4<285::Aid-sdr153>3.0.Co;2-f
Marr, B. (2015). *Big Data: Using SMART Big Data, Analytics and Metrics To Make Better Decisions and Improve Performance* (1st ed.). Chichester, UK: John Wiley & Sons.
Mihet, R., & Philippon, T. (2019). The Economics of Big Data and Artificial Intelligence. *Disruptive Innovation in Business and Finance in the Digital World (International Finance Review, Vol. 20), Emerald Publishing Limited*, 29-43.
Misiak, I. (2019). AI, Machine Learning, Personalization, and Automation: What's the Difference? Retrieved from https://elementthree.com/blog/ai-machine-learning-personalization-and-automation-whats-the-difference/
Montgomery, A. L., & Smith, M. D. (2009). Prospects for Personalization on the Internet. *Journal of Interactive Marketing, 23*(2), 130-137. doi:https://doi.org/10.1016/j.intmar.2009.02.001
Nair, H. S., Misra, S., IV, W. J. H., Mishra, R., & Acharya, A. (2017). Big Data and Marketing Analytics in Gaming: Combining Empirical Models and Field Experimentation. *Marketing Science, 36*(5), 699-725. doi:10.1287/mksc.2017.1039
Nicholson, C. F., & Kaiser, H. M. (2008). Dynamic market impacts of generic dairy advertising. *Journal of Business Research, 61*(11), 1125-1135. doi:https://doi.org/10.1016/j.jbusres.2007.11.011
Nicolle, A., Grzybowski, L., & Zulehner, C. (2018). IMPACT OF COMPETITION, INVESTMENT, AND REGULATION ON PRICES OF MOBILE SERVICES: EVIDENCE FROM FRANCE. *Economic Inquiry, 56*(2), 1322-1345. doi:10.1111/ecin.12547
Obermeyer, Z., & Emanuel, E. J. (2016). Predicting the Future - Big Data, Machine Learning, and Clinical Medicine. *The New England journal of medicine, 375*(13), 1216-1219. doi:10.1056/NEJMp1606181
Oliva, R. (2003). Model calibration as a testing strategy for system dynamics models. *European Journal of Operational Research, 151*(3), 552-568. doi:https://doi.org/10.1016/S0377-2217(02)00622-7
Oliva, R., Sterman, J. D., & Giese, M. (2003). Limits to growth in the new economy: exploring the 'get big fast' strategy in e-commerce. *System Dynamics Review, 19*(2), 83-117. doi:10.1002/sdr.271
Paich, M., & Sterman, J. D. (1993). Boom, Bust, and Failures to Learn in Experimental Markets. *Management Science, 39*(12), 1439-1458. doi:10.1287/mnsc.39.12.1439
Panoho, K. (2019). The Age of Analytics and The Importance of Data Quality. Retrieved from https://www.forbes.com/sites/forbesagencycouncil/2019/10/01/the-age-of-analytics-and-the-importance-of-data-quality/#499124ba5c3c
Park, C. H., Park, Y.-H., & Schweidel, D. A. (2018). The effects of mobile promotions on customer purchase dynamics. *International Journal of Research in Marketing, 35*(3), 453-470. doi:https://doi.org/10.1016/j.ijresmar.2018.05.001
Pechmann, C., & Stewart, D. W. (1988). Advertising Repetition: A Critical Review of Wearin and Wearout. *Current Issues and Research in Advertising, 11*(1-2), 285-329. doi:10.1080/01633392.1988.10504936
Peltier, J. W., Zahay, D., & Lehmann, D. R. (2013). Organizational Learning and CRM Success: A Model for Linking Organizational Practices, Customer Data Quality, and Performance. *Journal of Interactive Marketing, 27*(1), 1-13. doi:https://doi.org/10.1016/j.intmar.2012.05.001
Petrov, C. (2020). 25+ Impressive Big Data Statistics for 2020. Retrieved from https://techjury.net/blog/big-data-statistics/#gref
Pick, D., Thomas, J. S., Tillmanns, S., & Krafft, M. (2016). Customer win-back: the role of attributions and perceptions in customers' willingness to return. *Journal of the Academy of Marketing Science, 44*(2), 218-240. doi:10.1007/s11747-015-0453-6
Piekniewski, F. (2018). AI Winter Is Well On Its Way. Retrieved from https://blog.piekniewski.info/2018/05/28/ai-winter-is-well-on-its-way/
Rahmandad, H., & Sibdari, S. (2012). Joint pricing and openness decisions in software markets with reinforcing loops. *System Dynamics Review, 28*(3), 209-229. doi:10.1002/sdr.1473

Ramasamy, K. (2019). How Big Data Can Be A Big Problem. Retrieved from https://www.forbes.com/sites/forbestechcouncil/2019/07/26/how-big-data-can-be-a-big-problem/#526c557735c9

Rand, W., Rust, R. T., & Kim, M. (2018). Complex systems: marketing's new frontier. *AMS Review, 8*(3), 111-127. doi:10.1007/s13162-018-0122-2

Rigby, D. K., Reichheld, F. F., & Schefter, P. (2002). Avoid the Four Perils of CRM. *Harvard Business Review, 80*(2), 101-109.

Rogers, E. M. (1995). *Diffusion of Innovations* (4th ed.). New-York: The Free Press.

Romaniuk, J. (2012). Five Steps to Smarter Targeting. *Journal of Advertising Research, 52*(3), 288-290. doi:10.2501/jar-52-3-288-290

Rust, R. T. (2020). The future of marketing. *International Journal of Research in Marketing, 37*, 15-26. doi:https://doi.org/10.1016/j.ijresmar.2019.08.002

Saboo, A. R., Kumar, V., & Park, I. (2016). Using big data to model time-varying effects for marketing resource (re) allocation. *MIS Quarterly, 40*(4), 911-939.

Saleh, M., Oliva, R., Kampmann, C. E., & Davidsen, P. I. (2010). A comprehensive analytical approach for policy analysis of system dynamics models. *European Journal of Operational Research, 203*(3), 673-683. doi:https://doi.org/10.1016/j.ejor.2009.09.016

Schmidt, S., & Eisend, M. (2015). Advertising Repetition: A Meta-Analysis on Effective Frequency in Advertising. *Journal of Advertising, 44*(4), 415-428. doi:10.1080/00913367.2015.1018460

Seoul Urban Solutions Agency. (2016). Using Big Data to Support Small Businesses. Retrieved from https://development.asia/explainer/using-big-data-support-small-businesses

Shollo, A., & Galliers, R. D. (2016). Towards an understanding of the role of business intelligence systems in organisational knowing. *Information Systems Journal, 26*(4), 339-367. doi:10.1111/isj.12071

Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research, 104*, 333-339. doi:https://doi.org/10.1016/j.jbusres.2019.07.039

Statt, N. (2019). Verizon will now charge more money for in-store activations of new phones. Retrieved from https://www.theverge.com/2019/4/16/18411221/verizon-activation-fee-cost-increase-in-store-online-reduction

Sterman, J. (2000). *System Dynamics: Systems Thinking and Modeling for a Complex World*. US: McGraw-Hill Education.

Sterman, J., Richardson, G., & Davidsen, P. (1988). The dynamics of petroleum resource estimates in the United States: results of a synthetic experiment. *Technological Forecasting and Social Change, 34*, 219-249.

Sterman, J. D. (1984). Appropriate summary statistics for evaluating the historical fit of system dynamics models. *Dynamica, 10*(2), 51-66.

Sterman, J. D. (1989). Modeling Managerial Behavior: Misperceptions of Feedback in a Dynamic Decision Making Experiment. *Management Science, 35*(3), 321-339. doi:10.1287/mnsc.35.3.321

Sterman, J. D. (1992). *System Dynamics Modeling for Project Management*. Sloan School of Management, Massachusetts Institute of Technology. Cambridge MA.

Sterman, J. D. (1994). Learning in and about complex systems. *System Dynamics Review, 10*(2-3), 291-330. doi:10.1002/sdr.4260100214

Sterman, J. D. (2001). System Dynamics Modeling: Tools for Learning in a Complex World. *California Management Review, 43*(4), 8-25. doi:10.2307/41166098

Sterman, J. D., Henderson, R., Beinhocker, E. D., & Newman, L. I. (2007). Getting Big Too Fast: Strategic Dynamics with Increasing Returns and Bounded Rationality. *Management Science, 53*(4), 683-696. doi:10.1287/mnsc.1060.0673

Sterman, J. D., Repenning, N. P., & Kofman, F. (1997). Unanticipated Side Effects of Successful Quality Programs: Exploring a Paradox of Organizational Improvement. *Management Science, 43*(4), 503-521. doi:10.1287/mnsc.43.4.503

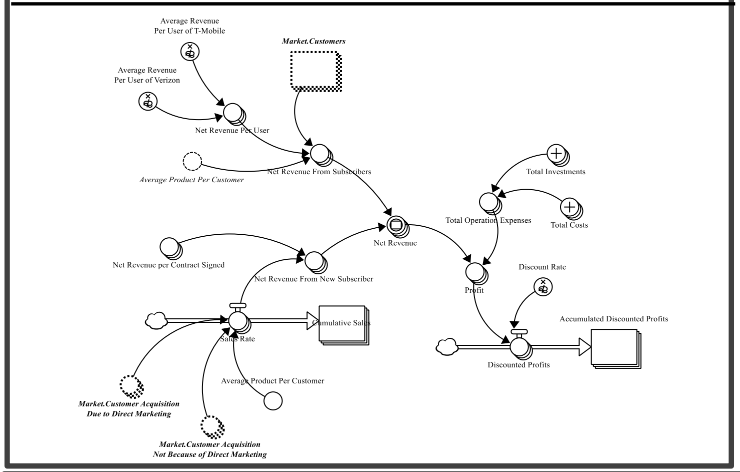
Sterman, J. D., Richardson, G. P., & Davidsen, P. (1988). Modeling the estimation of petroleum resources in the United States. *Technological Forecasting and Social Change, 33*(3), 219-249. doi:https://doi.org/10.1016/0040-1625(88)90015-7

Struben, J., & Sterman, J. D. (2008). Transition Challenges for Alternative Fuel Vehicle and Transportation Systems. *Environment and Planning B: Planning and Design, 35*(6), 1070-1097. doi:10.1068/b33022t
Surprenant, C. F., & Solomon, M. R. (1987). Predictability and Personalization in the Service Encounter. *Journal of Marketing, 51*(2), 86-96.
T-Mobile. (2007-2019). Annual Reports & Proxy Statements. Retrieved from https://investor.t-mobile.com/financial-performance/annual-reports-and-proxy-statements/default.aspx
Tambe, P. (2014). Big Data Investment, Skills, and Firm Value. *Management Science, 60*(6), 1452-1469. doi:10.1287/mnsc.2014.1899
Trusov, M., Bucklin, R. E., & Pauwels, K. (2009). Effects of Word-of-Mouth Versus Traditional Marketing: Findings from an Internet Social Networking Site. *Journal of Marketing, 73*(5), 90-102.
TRUSTe. (2016). U.S. consumer privacy index. Retrieved from https://www.trustarc.com/resources/privacy-research/ncsa-consumer-privacy-index-us/
Tucker, C. E. (2013). Social Networks, Personalized Advertising, and Privacy Controls. *Journal of Marketing Research, 51*(5), 546-562. doi:10.1509/jmr.10.0355
Turner, D., Schroeck, M., & Shockley, R. (2013). *Analytics: The real-world use of big data in financial services*. Retrieved from Executive Report, IBM Institute for Business Value and Saïd Business School, University of Oxford: https://www.ibm.com/downloads/cas/E4BWZ1PY
van de Weyer, C., & Costers, C. (2020). Three Ways Telcos Can Grow Their B2B Businesses. Retrieved from https://www.forbes.com/sites/baininsights/2016/06/14/three-ways-telcos-can-grow-their-b2b-businesses/#3122e82d59ec
van Diepen, M., Donkers, B., & Franses, P. H. (2009a). Does irritation induced by charitable direct mailings reduce donations? *International Journal of Research in Marketing, 26*(3), 180-188.
van Diepen, M., Donkers, B., & Franses, P. H. (2009b). Dynamic and Competitive Effects of Direct Mailings: A Charitable Giving Application. *Journal of Marketing Research, 46*(1), 120-133.
Verhoef, P., Kooge, E., & Walk, N. (2016). *Creating value with big data analytics: Making smarter marketing decisions*: Routledge.
Verizon. (2006-2019). Verizon annual reports. Retrieved from https://www.verizon.com/about/investors/annual-report
Vesanen, J. (2007). What is personalization? A conceptual framework. *European Journal of Marketing, 41*(5/6), 409-418. doi:10.1108/03090560710737534
Walther, G., Wansart, J., Kieckhäfer, K., Schnieder, E., & Spengler, T. S. (2010). Impact assessment in the automotive industry: mandatory market introduction of alternative powertrain technologies. *System Dynamics Review, 26*(3), 239-261. doi:10.1002/sdr.453
Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J.-f., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research, 70*, 356-365. doi:https://doi.org/10.1016/j.jbusres.2016.08.009
Wassouf, W. N., Alkhatib, R., Salloum, K., & Balloul, S. (2020). Predictive analytics using big data for increased customer loyalty: Syriatel Telecom Company case study. *Journal of Big Data, 7*(1), 29. doi:10.1186/s40537-020-00290-0
Xu, Z., Frankwick, G. L., & Ramirez, E. (2016). Effects of big data analytics and traditional marketing analytics on new product success: A knowledge fusion perspective. *Journal of Business Research, 69*(5), 1562-1566. doi:https://doi.org/10.1016/j.jbusres.2015.10.017
Yan, J., Liu, N., Wang, G., Zhang, W., Jiang, Y., & Chen, Z. (2009). *How much can behavioral targeting help online advertising?* Paper presented at the Proceedings of the 18th international conference on World wide web.
Yoo, J., & Park, M. (2016). The effects of e-mass customization on consumer perceived value, satisfaction, and loyalty toward luxury brands. *Journal of Business Research, 69*(12), 5775-5784. doi:https://doi.org/10.1016/j.jbusres.2016.04.174
Yu, H. (2019). Netflix Grows Subscriber Base, Thanks To Smart Algorithms And Human Creativity. Retrieved from https://www.forbes.com/sites/howardhyu/2019/01/17/investors-may-be-disappointed-but-netflix-will-keep-inventing-the-future/#40de9d702434

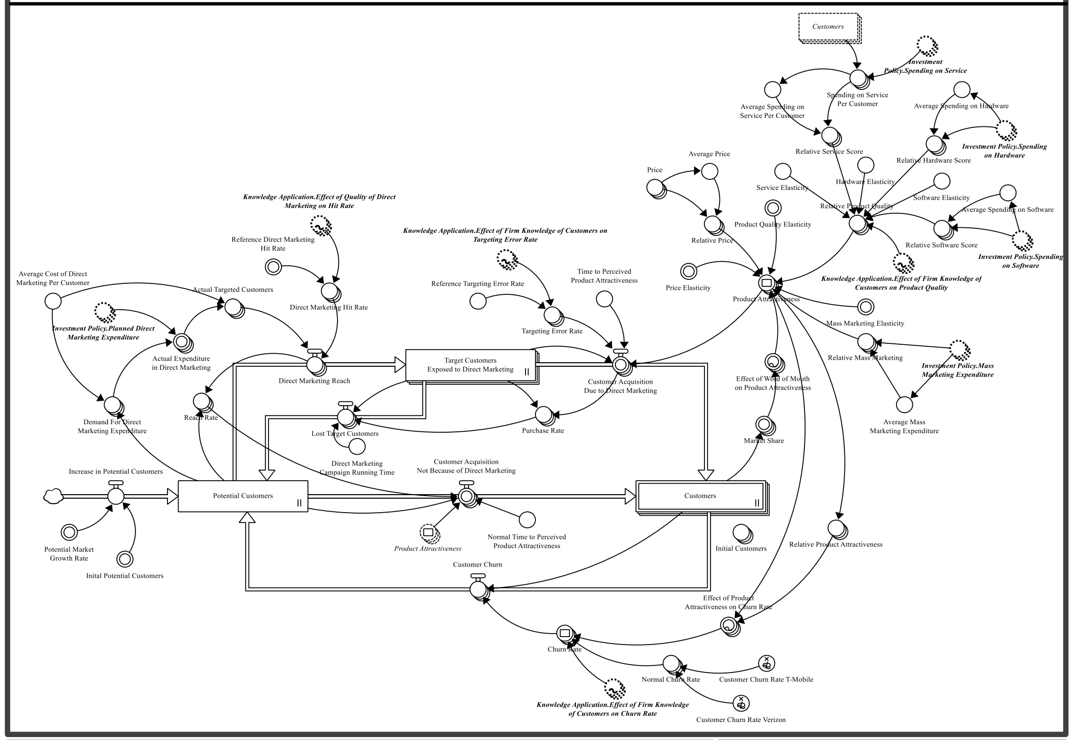
APPENDICES

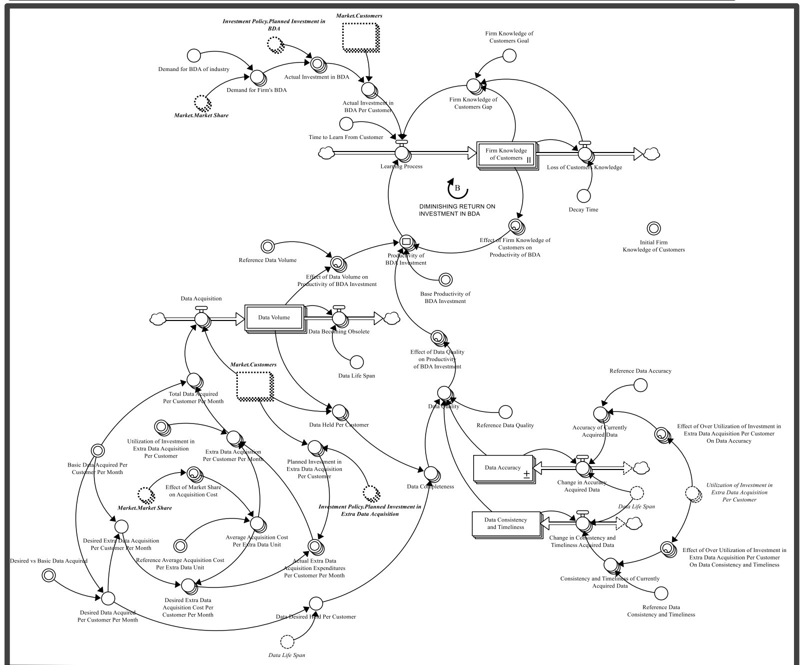
APPENDIX 1: Full Stock and Flow Diagram

Business Module

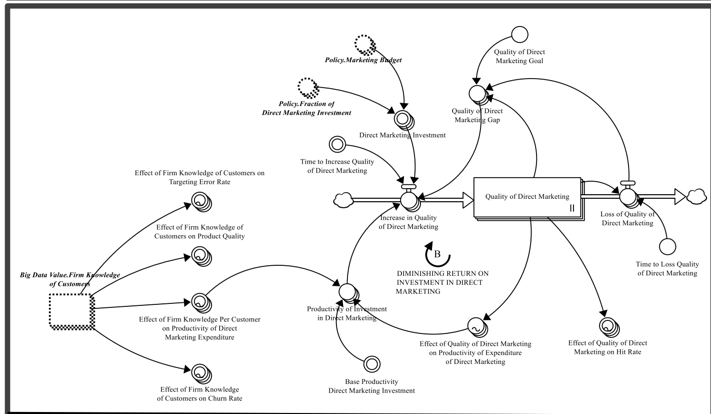


Market Module



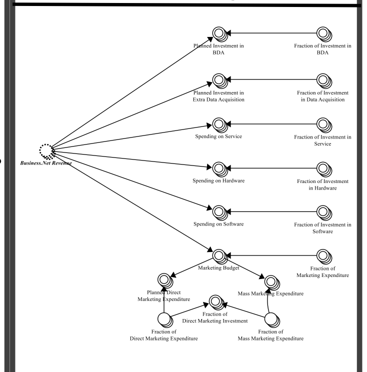


Big Data Value Module



Knowledge Application Module

Investment Policy Module



APPENDIX 2: List of Equations and Baseline Parameters

Name of element	Type	Equation/Value	Units	Documentation	Source
Top-Level Model:					
"Observed_Number_of_Customers_of_T-Mobile"	Graphical Function	GRAPH(TIME) Points: (0.00, 34000000.0), (3.11111111111, 44000000.0), (6.22222222222, 45000000.0), (9.33333333333, 46700000.0), (12.4444444444, 49100000.0), (15.5555555556, 50500000.0), (18.6666666667, 52900000.0), (21.7777777778, 55000000.0), (24.8888888889, 56700000.0), (28.00, 58900000.0), (31.1111111111, 61200000.0), (34.2222222222, 63300000.0), (37.3333333333, 65500000.0), (40.4444444444, 67400000.0), (43.5555555556, 69400000.0), (46.6666666667, 71500000.0), (49.7777777778, 72600000.0), (52.8888888889, 69600000.0), (56.00, 70700000.0), (59.1111111111, 72600000.0), (62.2222222222, 74000000.0), (65.3333333333, 75600000.0), (68.4444444444, 77200000.0), (71.5555555556, 79700000.0), (74.6666666667, 81300000.0), (77.7777777778, 83100000.0), (80.8888888889, 84200000.0), (84.00, 86000000.0)	person	Historical data	https://www.statista.com/statistics/219564/total-contract-customers-of-t-mobile-usa-by-quarter/
Observed_Number_of_Customers_of_Verizon	Graphical Function	GRAPH(TIME) Points: (0.00, 116750000.0), (3.11111111111, 118190000.0), (6.22222222222, 119450000.0), (9.33333333333, 121310000.0), (12.4444444444, 122000000.0), (15.5555555556, 123540000.0), (18.6666666667, 125290000.0), (21.7777777778, 131890000.0), (24.8888888889, 133480000.0), (28.00, 135440000.0), (31.1111111111, 137550000.0), (34.2222222222, 140100000.0), (37.3333333333, 141470000.0), (40.4444444444, 142750000.0), (43.5555555556, 143880000.0), (46.6666666667, 145740000.0), (49.7777777778, 146010000.0), (52.8888888889, 147240000.0), (56.00, 148870000.0), (59.1111111111, 150460000.0), (62.2222222222, 151480000.0), (65.3333333333, 152650000.0), (68.4444444444, 153970000.0), (71.5555555556, 153970000.0), (74.6666666667, 153970000.0), (77.7777777778, 153970000.0), (80.8888888889, 153970000.0), (84.00, 153970000.0)	person	Historical data	https://www.statista.com/statistics/283507/subscribers-to-top-wireless-carriers-in-the-us/
Observed_Operating_Income_of_T-Mobile"	Graphical Function	GRAPH(TIME) Points: (0.0, 98416666.67), (4.44444444444, 98416666.67), (8.88888888889, 98416666.67), (13.3333333333, 98416666.67), (17.7777777778, 147666666.7), (22.2222222222, 147666666.7), (26.6666666667, 147666666.7), (31.1111111111, 147666666.7), (35.5555555556, 206583333.3), (40.0, 206583333.3), (44.4444444444, 206583333.3), (48.8888888889, 206583333.3), (53.3333333333, 337500000.0), (57.7777777778, 337500000.0), (62.2222222222, 337500000.0), (66.6666666667, 337500000.0), (71.1111111111, 407333333.3), (75.5555555556, 407333333.3), (80.0, 407333333.3), (84.4444444444, 407333333.3), (88.8888888889, 442416666.7), (93.3333333333, 442416666.7), (97.7777777778, 442416666.7), (102.222222222, 442416666.7), (106.666666667, 476833333.3), (111.111111111, 476833333.3), (115.555555556, 476833333.3), (120.0, 476833333.3)	USD/month	Historical data	https://www.statista.com/statistics/219468/operating-income-of-t-mobile-usa-since-2005/

Name of element	Type	Equation/Value	Units	Documentation	Source
Observed_Operating_Income_of_Verizon	Graphical Function	GRAPH(TIME) Points: (0.0, 2261666667.0), (4.44444444444, 2261666667.0), (8.88888888889, 2261666667.0), (13.3333333333, 2261666667.0), (17.7777777778, 2261666667.0), (22.2222222222, 2261666667.0), (26.6666666667, 2261666667.0), (31.1111111111, 2261666667.0), (35.5555555556, 2551666667.0), (40.0, 2551666667.0), (44.4444444444, 2551666667.0), (48.8888888889, 2551666667.0), (53.3333333333, 2437500000.0), (57.7777777778, 2437500000.0), (62.2222222222, 2437500000.0), (66.6666666667, 2437500000.0), (71.1111111111, 2285833333.0), (75.5555555556, 2285833333.0), (80.0, 2285833333.0), (84.4444444444, 2285833333.0), (88.8888888889, 1856666667.0), (93.3333333333, 1856666667.0), (97.7777777778, 1856666667.0), (102.222222222, 1856666667.0), (106.666666667, 2531666667.0), (111.111111111, 2531666667.0), (115.555555556, 2531666667.0), (120.0, 2531666667.0)	USD/month	Historical data	https://www.statista.com/statistics/482797/verizon-communications-operating-income/
"Observed_Total_Revenue_of_T-Mobile"	Graphical Function	GRAPH(TIME) Points: (0.00, 1559000000.0), (3.11111111111, 2076000000.0), (6.22222222222, 2229333333.0), (9.33333333333, 2275666667.0), (12.4444444444, 2291666667.0), (15.5555555556, 2395000000.0), (18.6666666667, 2450000000.0), (21.7777777778, 2718000000.0), (24.8888888889, 2592666667.0), (28.00, 2726333333.0), (31.1111111111, 2616333333.0), (34.2222222222, 2749000000.0), (37.3333333333, 2888000000.0), (40.4444444444, 3095666667.0), (43.5555555556, 3101666667.0), (46.6666666667, 3411333333.0), (49.7777777778, 3204333333.0), (52.8888888889, 3404333333.0), (56.00, 3339666667.0), (59.1111111111, 3586333333.0), (62.2222222222, 3485000000.0), (65.3333333333, 3523666667.0), (68.4444444444, 3613000000.0), (71.5555555556, 3815000000.0), (74.6666666667, 3693333333.0), (77.7777777778, 3659666667.0), (80.8888888889, 3687000000.0), (84.00, 3959333333.0)	USD/month	Historical data	https://www.statista.com/statistics/219435/total-revenue-of-t-mobile-usa-by-quarter/
Observed_Total_Revenue_of_Verizon	Graphical Function	GRAPH(TIME) Points: (0.00, 6751666667.0), (3.11111111111, 6751666667.0), (6.22222222222, 6751666667.0), (9.33333333333, 6751666667.0), (12.4444444444, 7304166667.0), (15.5555555556, 7304166667.0), (18.6666666667, 7304166667.0), (21.7777777778, 7304166667.0), (24.8888888889, 7640000000.0), (28.00, 7640000000.0), (31.1111111111, 7640000000.0), (34.2222222222, 7640000000.0), (37.3333333333, 7432500000.0), (40.4444444444, 7432500000.0), (43.5555555556, 7432500000.0), (46.6666666667, 7432500000.0), (49.7777777778, 7292500000.0), (52.8888888889, 7292500000.0), (56.00, 7292500000.0), (59.1111111111, 7292500000.0), (62.2222222222, 7644166667.0), (65.3333333333, 7644166667.0), (68.4444444444, 7644166667.0), (71.5555555556, 7644166667.0), (74.6666666667, 7588333333.0), (77.7777777778, 7588333333.0), (80.8888888889, 7588333333.0), (84.00, 7588333333.0)	USD/month	Historical data	https://www.statista.com/statistics/199786/total-operating-revenues-of-us-telecommunication-providers/
Policy_Start_Time	Constant	84	Months	The time at which the chosen policy starts being implemented	Assumption/Calibration
"Policy_Status_T-Mobile_Reaction_1"	Variable	IF("Policy_Switch_T-Mobile_Reaction_1"=1)AND(Policy_Start_Time<TIME) THEN(1)ELSE(0)	Unitless	Dummy variable used to show whether the policy T-Mobile Reaction 1 is being active: 1 = active, 0 = inactive	Obvious calculation/ General fact

Name of element	Type	Equation/Value	Units	Documentation	Source
"Policy_Status_T-Mobile_Reaction_2"	Variable	IF("Policy_Switch_T-Mobile_Reaction_2"=1)AND(Policy_Start_Time<TIME) THEN(1)ELSE(0)	Dimensionless	Dummy variable used to show whether the policy T-Mobile Reaction 2 is being active: 1 = active, 0 = inactive	Obvious calculation/ General fact
Policy_Status_Verizon	Variable	IF(Policy_Switch_Verizon=1)AND(Policy_Start_Time<TIME) THEN(1)ELSE(0)	Dimensionless	Dummy variable used to show whether the policy Verizon First Move is being active: 1 = active, 0 = inactive	Obvious calculation/ General fact
"Policy_Switch_T-Mobile_Reaction_1"	Variable	0	Dimensionless	Dummy variable used to activate the policy called T-Mobile Reaction 1: 1 = activated, 0 = deactivated	Assumption/Calibration
"Policy_Switch_T-Mobile_Reaction_2"	Variable	0	Dimensionless	Dummy variable used to activate the policy called T-Mobile Reaction 2: 1 = activated, 0 = deactivated	Assumption/Calibration
Policy_Switch_Verizon	Variable	0	Dimensionless	Dummy variable used to activate the policy called Verizon First Move: 1 = activated, 0 = deactivated	Assumption/Calibration
Scenario_Start_Time	Constant	84	Months	The time at which the chosen scenario starts being implemented	Assumption/Calibration
Scenario_Status_BDA_Explosion	Variable	IF(Scenario_switch_1=1)AND(Scenario_Start_Time<TIME) THEN(1)ELSE(0)	Dimensionless	Dummy variable used to show whether the scenario BDA Explosion is being active: 1 = active, 0 = inactive	Obvious calculation/ General fact
Scenario_Status_BDA_Winter	Variable	IF(Scenario_switch_2=1)AND(Scenario_Start_Time<TIME) THEN(1)ELSE(0)	Dimensionless	Dummy variable used to show whether the scenario BDA Winter is being active: 1 = active, 0 = inactive	Obvious calculation/ General fact
Scenario_switch_BDA_Explosion	Variable	0	Dimensionless	Dummy variable used to activate the scenario called BDA Explosion: 1 = activated, 0 = deactivated	Assumption/Calibration
Scenario_switch_BDA_Winter	Variable	0	Dimensionless	Dummy variable used to activate the scenario called BDA Winter: 1 = activated, 0 = deactivated	Assumption/Calibration
Big_Data_Value:					
Data_Accuracy[Company](t)	Stock	Data_Accuracy[Company](t - dt) + (Change_in_Accuracy_Acquired_Data[Company]) * dt Initial value = 1	Dimensionless	The accuracy of the firm's database accumulated from the beginning (2013) (array)	Assumption/Calibration
Data_Consistency_and_Timeliness[Company](t)	Stock	Data_Consistency_and_Timeliness[Company](t - dt) + (Change_in_Consistency_and_Timeliness_Acquired_Data[Company]) * dt Initial value = 1	Dimensionless	The consistency and timeliness of the firm's database accumulated from the beginning (2013) (array)	Assumption/Calibration
Data_Volume[Company](t)	Stock	Data_Volume[Company](t - dt) + (Data_Acquisition[Company] - Data_Becoming_Obsolete[Company]) * dt Initial value = 1	GB	The amount of data that the firm has accumulated from the beginning (2013) (array)	Assumption/Calibration
Firm_Knowledge_of_Customers[Company](t)	Stock	Firm_Knowledge_of_Customers[Company](t - dt) + (Learning_Process[Company] - Loss_of_Customers_Knowledge[Company]) * dt Initial Firm Knowledge of Customers = 0.05	Dimensionless/ person	The firm' knowledge of each customer (i.e., customer insights) on average accumulated over time (array)	Vernon, M. (2012). Implications of The Rate of Organizational Learning on Value Capture in the Digital

Name of element	Type	Equation/Value	Units	Documentation	Source
					Economy. In Proceedings of the 31st International Conference of the System Dynamics Society, USA.
Change_in_Accuracy_Acquired_Data[Company]	Biflow	(Accuracy_of_Currently_Acquired_Data-Data_Accuracy)/Data_Life_Span	Dimensionless/ Months	It refers to how much the accuracy of the firm's database increases (or decreases) every month (array)	Obvious calculation/ General fact
Change_in_Consistency_and_Timeliness_Acquired_Data[Company]	Biflow	(Consistency_and_Timeliness_of_Currently_Acquired_Data-Data_Consistency_and_Timeliness)/ Data_Life_Span	Dimensionless/ Months	It refers to how much the consistency and timeliness of the firm's database increases (or decreases) every month (array)	Obvious calculation/ General fact
Data_Acquisition[Company]	Inflow	Market.Customers* Total_Data_Acquired_Per_Customer_Per_Month	GB/Months	The data that the firm gains per month (array)	Obvious calculation/ General fact
Data_Becoming_Obsolete[Company]	Outflow	Data_Volume/ Data_Life_Span	GB/Months	It refers to the monthly decrease in the data volume caused by time (e.g., the obsolescence of data) (array)	Obvious calculation/ General fact
Learning_Process[Company]	Inflow	MIN(DELAY3 (Productivity_of_BDA_Investment*Actual_Investment_in_BDA_Per_Customer, Time_to_Learn_From_Customer), Firm_Knowledge_of_Customers_Gap/Time_to_Learn_From_Customer)	dmnl/person/Months	The knowledge about customers that the firm gains per month per customer (array)	Obvious calculation/ General fact
Loss_of_Customers_Knowledge[Company]	Outflow	Firm_Knowledge_of_Customers/ Decay_Time	dmnl/person/Months	It refers to the monthly decrease in the firm's knowledge of customers caused by time (e.g., the obsolescence of knowledge) (array)	Obvious calculation/ General fact
Accuracy_of_Currently_Acquired_Data[Company]	Variable	Reference_Data_Accuracy*Effect_of_Over_Utilization_of_Investment_in_Extra_Data_Acquisition_Per_Customer_On_Data_Accuracy	Dimensionless	The accuracy of the database which is affected by over utilization of investment in extra data acquisition	Obvious calculation/ General fact
Actual_Extra_Data_Acquisition_Expenditures_Per_Customer_Per_Month[Company]	Variable	MIN (Planned_Investment_in_Extra_Data_Acquisition_Per_Customer, Desired_Extra_Data_Acquisition_Cost_Per_Customer_Per_Month)	USD/person/Months	The monthly amount of investment in extra data per customer actually spent by the firm (array)	Obvious calculation/ General fact
Actual_Investment_in_BDA[Company]	Variable	MIN(Investment_Policy.Planned_Investment_in_BDA, Demand_for_Firm's_BDA)	USD/Months	The actual money invested in big data analytics (BDA) per month (array)	Obvious calculation/ General fact
Actual_Investment_in_BDA_Per_Customer[Company]	Variable	Actual_Investment_in_BDA/ Market.Customers	USD/person/Months	The actual money invested in big data analytics (BDA) per month per customer (array)	Obvious calculation/ General fact
Average_Acquisition_Cost_Per_Extra_Data_Unit[Company]	Variable	Reference_Average_Acquisition_Cost_Per_Extra_Data_Unit* Effect_of_Market_Share_on_Acquisition_Cost	USD/GB	The actual cost of data acquisition that the firm spends on per each data unit	Obvious calculation/ General fact
Base_Productivity_of_BDA_Investment	Constant	0.06	1/USD	The maximum productivity of BDA investment in case the quality of big data is maximum, the data volume is maximum, and the firm's knowledge of customers is minimum	Bughin, J. (2016). Big data, Big bang?. Journal of Big Data, 3(1), 2.

Name of element	Type	Equation/Value	Units	Documentation	Source
Basic_Data_Acquired_Per_Customer_Per_Month	Variable	IF (.Scenario_Status_BDA_Explosion+.Scenario_Status_BDA_Winter = 0) THEN 1.7 ELSE (IF(.Scenario_Status_BDA_Explosion=1) THEN (1.7*1.5) ELSE (1.7*0.5))	GB/person/Months	Total amount of basic data that the firm acquires per each customer per month (used for senario analysis)	Assumption/Calibration
Consistency_and_Timeliness_of_Currently_Acquired_Data[Company]	Variable	Reference_Data_Consistency_and_Timeliness*Effect_of_Over_Utilization_of_Investment_in_Extra_Data_Acquisition_Per_Customer_On_Data_Consistency_and_Timeliness	Dimensionless	The consistency and timeliness of the database which is affected by over utilization of investment in extra data acquisition	Obvious calculation/ General fact
Data_Completeness[Company]	Variable	Data_Held_Per_Customer/Data_Desired_Held_Per_Customer	Dimensionless	Data completeness is the ratio of actual amount of data acquired per customer to the amount of data that the firm desires to have about each customer.	Obvious calculation/ General fact
Data_Desired_Held_Per_Customer	Variable	Desired_Data_Acquired_Per_Customer_Per_Month*Data_Life_Span	GB/person	The average data amount that the firm desires to have about each customer	Obvious calculation/ General fact
Data_Held_Per_Customer[Company]	Variable	Data_Volume/Market.Customers	GB/person	It refers to how much data that the firm has acquired per each customer on average	Obvious calculation/ General fact
Data_Life_Span	Constant	12	Months	The number of months until the firm's data volume is reduced by one unit	Obvious calculation/ General fact
Data_Quality[Company]	Variable	Reference_Data_Quality* Data_Completeness* Data_Accuracy* Data_Consistency_and_Timeliness	Dimensionless	The quality of the firm's database	Obvious calculation/ General fact
Decay_Time	Constant	48	Months	The number of months until the firm's knowledge of customers is reduced by one unit	Assumption/Calibration
Demand_for_BDA_of_industry	Constant	4560000000	USD/Months	The desired amount of money needed to invest in big data analytics (BDA) for the whole market per month (array)	https://www.visualcapitalist.com/80-trillion-world-economy-one-chart/ https://www.statista.com/statistics/248004/percentage-added-to-the-us-gdp-by-industry/
Demand_for_Firm's_BDA[Company]	Variable	Demand_for_BDA_of_industry* Market.Market_Share/100	USD/Months	The desired amount of money needed to invest in big data analytics (BDA) for the firm per month (array)	Obvious calculation/ General fact
Desired_Data_Acquired_Per_Customer_Per_Month	Variable	Basic_Data_Acquired_Per_Customer_Per_Month*Desired_vs_Basic_Data_Acquired	GB/person/Months	It refers to how much data the firm desires to have about each customer on average per month	Obvious calculation/ General fact
Desired_Extra_Data_Acquisition_Cost_Per_Customer_Per_Month[Company]	Variable	Desired_Extra_Data_Acquisition_Per_Customer_Per_Month* Average_Acquisition_Cost_Per_Extra_Data_Unit	USD/person/Months	It refers to the expenses that the firm needs to pay if they want to collect all the extra data they desire to have. It is computed per customer per month.	Obvious calculation/ General fact
Desired_Extra_Data_Acquisition_Per_Customer_Per_Month	Variable	Desired_Data_Acquired_Per_Customer_Per_Month-Basic_Data_Acquired_Per_Customer_Per_Month	GB/person/Months	It refers to how much extra data the firm desires to have about each customer on average per month	Obvious calculation/ General fact

Name of element	Type	Equation/Value	Units	Documentation	Source
Desired_vs_Basic_Data_Acquired	Constant	4	Dimensionless	The ratio of basic data amount to desired data amount that the firm needs from customers	Assumption/Calibration
Effect_of_Data_Quality_on_Productivity_of_BDA_Investment[Company]	Graphical Function	GRAPH(Data_Quality) Points: (0.000, 0.0573241758989), (0.100, 0.0962155417107), (0.200, 0.157095468885), (0.300, 0.246011283551), (0.400, 0.363547459718), (0.500, 0.500), (0.600, 0.636452540282), (0.700, 0.753988716449), (0.800, 0.842904531115), (0.900, 0.903784458289), (1.000, 0.942675824101)	Dimensionless	A graphical function representing the effect of data quality on the productivity of BDA investment (array)	Assumption/Calibration
Effect_of_Data_Volume_on_Productivity_of_BDA_Investment[Company]	Graphical Function	GRAPH(Data_Volume/ Reference_Data_Volume) Points: (0.000, 0.0265969935769), (0.0555555555556, 0.0391657227968), (0.111111111111, 0.0573241758989), (0.166666666667, 0.0831726964939), (0.222222222222, 0.119202922022), (0.277777777778, 0.167981614866), (0.333333333333, 0.231475216501), (0.388888888889, 0.310025518872), (0.444444444444, 0.401312339888), (0.500, 0.500), (0.555555555556, 0.598687660112), (0.611111111111, 0.689974481128), (0.666666666667, 0.768524783499), (0.722222222222, 0.832018385134), (0.777777777778, 0.880797077978), (0.833333333333, 0.916827303506), (0.888888888889, 0.942675824101), (0.944444444444, 0.960834277203), (1.000, 0.973403006423)	Dimensionless	A graphical function representing the effect of data volume on productivity of BDA investment (array)	Assumption/Calibration
Effect_of_Firm_Knowledge_of_Customers_on_Productivity_of_BDA[Company]	Graphical Function	GRAPH(Firm_Knowledge_of_Customers) Points: (0.000, 1.000), (0.0526315789474, 0.987368421053), (0.105263157895, 0.971461988304), (0.157894736842, 0.951702786378), (0.210526315789, 0.926429308566), (0.263157894737, 0.893715170279), (0.315789473684, 0.851849329205), (0.368421052632, 0.799609113281), (0.421052631579, 0.736425709825), (0.473684210526, 0.662510121457), (0.526315789474, 0.578975946654), (0.578947368421, 0.48796369506), (0.631578947368, 0.392739699929), (0.684210526316, 0.297711042312), (0.736842105263, 0.20826625387), (0.789473684211, 0.130319917441), (0.842105263158, 0.0694076367389), (0.894736842105, 0.019), (0.947368421053, 0.005), (1.000, 0.000)	Dimensionless	A graphical function representing the effect of the firm's knowledge of customers on productivity of BDA (array)	Assumption/Calibration
Effect_of_Market_Share_on_Acquisition_Cost[Company]	Graphical Function	GRAPH(Market.Market_Share) Points: (0.0, 1.000), (10.0, 1.000), (20.0, 1.000), (30.0, 0.987), (40.0, 0.974), (50.0, 0.956), (60.0, 0.917), (70.0, 0.877), (80.0, 0.803), (90.0, 0.689), (100.0, 0.504)	Dimensionless	A graphical function representing the effect of market share on the data acquisition cost: costs reduce when the firm collects data about more customers (i.e., economies of scale) (array)	Assumption/Calibration
Effect_of_Over_Utilization_of_Investment_in_Extra_Data_Acquisition_Per_Customer_On_Data_Accuracy[Company]	Graphical Function	GRAPH(Utilization_of_Investment_in_Extra_Data_Acquisition_Per_Customer) Points: (0.000, 1.000), (0.500, 1.000), (1.000, 1.000), (1.500, 0.984), (2.000, 0.963), (2.500, 0.899), (3.000, 0.711), (3.500, 0.439), (4.000, 0.139), (4.500, 0.035), (5.000, 0.000)	Dimensionless	A graphical function representing the effect of over utilization of investment in extra data acquisition on data accuracy. Specifically, with the same amount of investment, the more data the firm acquires, the less the accuracy is. (array)	Assumption/Calibration
Effect_of_Over_Utilization_of_Investment_in_Extra_Data_Acquisition_Per_Customer_On_Data_Consistency_and_Timeliness[Company]	Graphical Function	GRAPH(Utilization_of_Investment_in_Extra_Data_Acquisition_Per_Customer) Points: (0.000, 1.000), (0.500, 1.000), (1.000, 1.000), (1.500, 0.984), (2.000, 0.963), (2.500, 0.925), (3.000, 0.868), (3.500, 0.798), (4.000, 0.649), (4.500, 0.412), (5.000, 0.000)	Dimensionless	A graphical function representing the effect of over utilization of investment in extra data acquisition on data consistency and timeliness. Specifically, with the same amount of investment, the more data the firm acquires, the less the consistency and timeliness is. (array)	Assumption/Calibration

Name of element	Type	Equation/Value	Units	Documentation	Source
Extra_Data_Acquisition_Per_Customer_Per_Month[Company]	Variable	Utilization_of_Investment_in_Extra_Data_Acquisition_Per_Customer* Actual_Extra_Data_Acquisition_Expenditures_Per_Customer_Per_Month/Average_Acquisition_Cost_Per_Extra_Data_Unit	GB/person/Months	Total amount of extra data that the firm acquires per each customer per month	Obvious calculation/ General fact
Firm_Knowledge_of_Customers_Gap[Company]	Variable	Firm_Knowledge_of_Customers_Goal-Firm_Knowledge_of_Customers+Loss_of_Customers_Knowledge*DT	Dimensionless/ person	A variable used in the normalization of the firm's knowledge of customers (array)	Obvious calculation/ General fact
Firm_Knowledge_of_Customers_Goal	Constant	1	Dimensionless/ person	A variable used in the normalization of the firm's knowledge of customers	Obvious calculation/ General fact
Initial_Firm_Knowledge_of_Customers	Constant	0.05	Dimensionless/ person	The firm' initial knowledge of each customer (i.e., customer insights) without investing in BDA	Vernon, M. (2012). Implications of The Rate of Organizational Learning on Value Capture in the Digital Economy. In Proceedings of the 31st International Conference of the System Dynamics Society, USA.
Planned_Investment_in_Extra_Data_Acquisition_Per_Customer[Company]	Variable	Investment_Policy.Planned_Investment_in_Extra_Data_Acquisition/Market.Customers	USD/person/Months	The monthly amount of investment in extra data per customer planned by the firm (array)	Obvious calculation/ General fact
Productivity_of_BDA_Investment[Company]	Variable	SMTHN (Base_Productivity_of_BDA_Investment*Effect_of_Firm_Knowledge_of_Customers_on_Productivity_of_BDA* Effect_of_Data_Quality_on_Productivity_of_BDA_Investment*Effect_of_Data_Volume_on_Productivity_of_BDA_Investment, 3, Base_Productivity_of_BDA_Investment)	1/USD	It refers to the extent to which the firm's knowledge of customers increases caused by one dollar of investment in BDA (array)	Obvious calculation/ General fact
Reference_Average_Acquisition_Cost_Per_Extra_Data_Unit	Variable	IF (.Scenario_Status_BDA_Explosion+.Scenario_Status_BDA_Winter = 0) THEN 3 ELSE (IF(.Scenario_Status_BDA_Explosion=1) THEN (3*0.5) ELSE (3*1.5))	USD/GB	The average cost of data acquisition per each data unit (used for scenario analysis)	Assumption/Calibration
Reference_Data_Accuracy	Constant	1	Dimensionless	The maximum data accuracy that the firm can have	Assumption/Calibration
Reference_Data_Consistency_and_Timeliness	Constant	1	Dimensionless	The maximum data consistency and timeliness that the firm can have	Assumption/Calibration
Reference_Data_Quality	Constant	1	Dimensionless	The maximum data quality that the firm can have	Assumption/Calibration
Reference_Data_Volume	Constant	2*10^10	GB	The maximum data volume that the firm gains (used for normalization)	Assumption/Calibration

Name of element	Type	Equation/Value	Units	Documentation	Source
Time_to_Learn_From_Customer	Constant	6	month	The number of months the knowledge learned about customers needs to take effect.	Assumption/Calibration
Total_Data_Acquired_Per_Customer_Per_Month[Company]	Variable	Basic_Data_Acquired_Per_Customer_Per_Month+ Extra_Data_Acquisition_Per_Customer_Per_Month	GB/person/Months	Total amount of data that the firm acquires per each customer per month	Obvious calculation/ General fact
Utilization_of_Investment_in_Extra_Data_Acquisition_Per_Customer[T_Mobile]	Variable	(1-."Policy_Status_T-Mobile_Reaction_1"-."Policy_Status_T-Mobile_Reaction_2")*1+ ."Policy_Status_T-Mobile_Reaction_1"*3+ ."Policy_Status_T-Mobile_Reaction_2"*4	Dimensionless	It refers to how the firm utilizes the investment in extra data acquisition in trading data quality for data volume. It is assumed that when this value is 1, no data quality is traded for data volume. When it is larger than 1, the larger it is , the more data quality is traded for data volume. This is used for policy analysis.	Assumption/Calibration
Utilization_of_Investment_in_Extra_Data_Acquisition_Per_Customer[Verizon]	Variable	(1-.Policy_Status_Verizon)*1+ .Policy_Status_Verizon*3	Dimensionless	It refers to how the firm utilizes the investment in extra data acquisition in trading data quality for data volume. It is assumed that when this value is 1, no data quality is traded for data volume. When it is larger than 1, the larger it is , the more data quality is traded for data volume. This is used for policy analysis.	Assumption/Calibration
Business:					
Accumulated_Discounted_Profits[Company](t)	Stock	Accumulated_Discounted_Profits[Company](t - dt) + (Discounted_Profits[Company]) * dt Initial value = 0	USD	Total expected present value of net profits per month accumulated since the beginning (2013)	Obvious calculation/ General fact
Cumulative_Sales[Company](t)	Stock	Cumulative_Sales[Company](t - dt) + (Sales_Rate[Company]) * dt Initial value = 0	Contract	Number of new subscriptions the firm acquires per month accumulated since the beginning (2013)	Obvious calculation/ General fact
Discounted_Profits[Company]	Inflow	EXP(-Discount_Rate * (204-TIME)) *Profit	$/Months	Expected present value of net profit per month computed based on Oliva et al. (2003, equation 12, page 92)	Oliva, R., Sterman, J.D. and Giese, M. (2003), Limits to growth in the new economy: exploring the 'get big fast' strategy in e-commerce. Syst. Dyn. Rev., 19: 83-117. doi:10.1002/sdr.271
Sales_Rate[Company]	Inflow	(Market.Customer_Acquisition_Due_to_Direct_Marketing+ Market.Customer_Acquisition_Not_Because_of_Direct_Marketing)* Average_Product_Per_Customer	Contract/Months	Total number of newly signed subscriptions per month (array)	Obvious calculation/ General fact
Actual_Firm_Expenditure_on_Collecting_Extra_Data[Company]	Variable	Big_Data_Value.Actual_Extra_Data_Acquisition_Expenditures_Per_Customer_Per_Month* Market.Customers	USD/Months		Obvious calculation/ General fact

Name of element	Type	Equation/Value	Units	Documentation	Source
Average_Product_Per_Customer	Constant	1	Contract/persons	Number of subscriptions per customer (same for both firms)	Assumption/Calibration
"Average_Revenue_Per_User_of_T-Mobile"	Graphical Function	GRAPH(TIME) Points: (0.00, 48.44246229), (3.11111111111, 45.98669074), (6.22222222222, 45.66826601), (9.33333333333, 44.9634302), (12.4444444444, 44.77052249), (15.5555555556, 44.58574622), (18.6666666667, 45.15417574), (21.7777777778, 44.22797775), (24.8888888889, 43.2566767), (28.00, 44.44947216), (31.1111111111, 44.19065468), (34.2222222222, 44.32549325), (37.3333333333, 43.10060968), (40.4444444444, 43.78007042), (43.5555555556, 44.42789265), (46.6666666667, 44.6550625), (49.7777777778, 44.25684552), (52.8888888889, 44.04317922), (56.00, 44.07488468), (59.1111111111, 43.65195776), (62.2222222222, 43.95737976), (65.3333333333, 43.75869875), (68.4444444444, 43.52460547), (71.5555555556, 43.66680187), (74.6666666667, 43.31214568), (77.7777777778, 43.30607308), (80.8888888889, 43.70115153), (84.00, 43.55439892)	USD/Contract/Months	Average revenue per subscriber per month for T-Mobile	https://www.statista.com/statistics/483672/t-mobile-us-postpaid-prepaid-arpu/
Average_Revenue_Per_User_of_Verizon	Graphical Function	GRAPH(TIME) Points: (0.00, 54.67), (3.11111111111, 55.0), (6.22222222222, 55.57), (9.33333333333, 55.46), (12.4444444444, 55.78), (15.5555555556, 55.42), (18.6666666667, 55.52), (21.7777777778, 54.15), (24.8888888889, 52.72), (28.00, 51.55), (31.1111111111, 50.74), (34.2222222222, 48.95), (37.3333333333, 47.49), (40.4444444444, 47.07), (43.5555555556, 46.74), (46.6666666667, 45.54), (49.7777777778, 43.82), (52.8888888889, 43.82), (56.00, 43.82), (59.1111111111, 43.82), (62.2222222222, 43.82), (65.3333333333, 42.43), (68.4444444444, 42.43), (71.5555555556, 42.43), (74.6666666667, 42.43), (77.7777777778, 42.43), (80.8888888889, 42.43), (84.00, 42.43)	USD/Contract/Months	Average revenue per subscriber per month for Verizon	https://www.statista.com/statistics/283513/arpu-top-wireless-carriers-us/
Average_Storage_Cost_Per_Data_Unit[Company]	Variable	Reference_Storage_Cost_Per_Data_Unit* Effect_of_Data_Volume_on_Average_Storage_Cost_Per_Data_Unit	USD/GB/Months	Average cost for data storage per data unit per month (array)	Obvious calculation/ General fact
Data_Storage_Cost_Per_Month[Company]	Variable	Big_Data_Value.Data_Volume* Average_Storage_Cost_Per_Data_Unit	USD/Months	Total costs for data storage per month	Obvious calculation/ General fact
Discount_Rate	Graphical Function	GRAPH(TIME) Points: (0.00, 0.034366083), (3.11111111111, 0.047739147), (6.22222222222, 0.047739147), (9.33333333333, 0.047739147), (12.4444444444, 0.047739147), (15.5555555556, 0.047739147), (18.6666666667, 0.047739147), (21.7777777778, 0.047739147), (24.8888888889, 0.047739147), (28.00, 0.047739147), (31.1111111111, 0.047739147), (34.2222222222, 0.047739147), (37.3333333333, 0.047739147), (40.4444444444, 0.047739147), (43.5555555556, 0.047739147), (46.6666666667, 0.047739147), (49.7777777778, 0.0541788542348), (52.8888888889, 0.059463094), (56.00, 0.059463094), (59.1111111111, 0.069913194), (62.2222222222, 0.0819634587056), (65.3333333333, 0.087955314), (68.4444444444, 0.0967658644426), (71.5555555556, 0.109539017277), (74.6666666667, 0.116441416), (77.7777777778, 0.122462048), (80.8888888889, 0.118799780324), (84.00, 0.103206842)	Dimensionless	Monthly discount rates calculated based on Federal Reserve Economic Data	https://fred.stlouisfed.org

Name of element	Type	Equation/Value	Units	Documentation	Source
Effect_of_Data_Volume_on_Average_Storage_Cost_Per_Data_Unit[Company]	Graphical Function	GRAPH(Big_Data_Value.Data_Volume/ Big_Data_Value.Reference_Data_Volume) Points: (0.000, 1.000), (0.100, 1.000), (0.200, 1.000), (0.300, 0.891), (0.400, 0.706), (0.500, 0.507), (0.600, 0.408), (0.700, 0.299), (0.800, 0.237), (0.900, 0.190), (1.000, 0.152)	Dimensionless	A graphical function representing the effect of data volume on data storage cost. Specifically, the larger the data volume, the lower the storage cost (i.e., economies of scale) (array)	Assumption/Calibration
Net_Revenue[T_Mobile]	Variable	SMTH3((Net_Revenue_From_New_Subscriber[T_Mobile]+Net_Revenue_From_Subscribers[T_Mobile]), 1, 1559000000)	USD/Months	Total monthly revenue used to decide the amount of investments, which is the total revenues from all (new and existing) subscriptions per month delayed by one period (1 month) (array)	https://www.statista.com/statistics/219435/total-revenue-of-t-mobile-usa-by-quarter/
Net_Revenue[Verizon]	Variable	SMTH3((Net_Revenue_From_New_Subscriber[Verizon]+Net_Revenue_From_Subscribers[Verizon]), 1, 6751666666)	USD/Months	Total monthly revenue used to decide the amount of investments, which is the total revenues from all (new and existing) subscriptions per month delayed by one period (1 month) (array)	https://www.statista.com/statistics/199786/total-operating-revenues-of-us-telecommunication-providers/
Net_Revenue_From_New_Subscriber[Company]	Variable	Sales_Rate* Net_Revenue_per_Contract_Signed	USD/Months	Total revenue generated from all newly signed subscriptions that the firm acquires per month (array)	Obvious calculation/ General fact
Net_Revenue_From_Subscribers[Company]	Variable	Market.Customers* Net_Revenue_Per_User* Average_Product_Per_Customer	USD/Months	Total revenue generated from all existing subscriptions the firm has per month (array)	Obvious calculation/ General fact
Net_Revenue_per_Contract_Signed[T_Mobile]	Constant	10	USD/Contract	Revenue generated per each new subscription (e.g., startup fee) (array)	https://www.reviews.org/mobile/best-cell-phone-plans/
Net_Revenue_per_Contract_Signed[Verizon]	Constant	20	USD/Contract	Revenue generated per each new subscription (e.g., startup fee) (array)	https://www.reviews.org/mobile/best-cell-phone-plans/
Net_Revenue_Per_User[T_Mobile]	Historical Data	"Average_Revenue_Per_User_of_T-Mobile"	USD/contract/ Months	Average revenue per subscriber per month (array)	https://www.statista.com/statistics/483672/t-mobile-us-postpaid-prepaid-arpu/
Net_Revenue_Per_User[Verizon]	Historical Data	Average_Revenue_Per_User_of_Verizon	USD/contract/ Months	Average revenue per subscriber per month (array	https://www.statista.com/statistics/283513/arpu-top-wireless-carriers-us/
Profit[T_Mobile]	Variable	Net_Revenue - Total_Operation_Expenses	USD/Months	Net profit of the firm per month (array).	Obvious calculation/ General fact
Profit[Verizon]	Variable	(Net_Revenue*1.2 - Total_Operation_Expenses)	USD/Months	Net profit of the firm per month (array). Note: In this thesis, I focus only on wireless services offered by the two firms. However, for Verizon Wireless, which is a division of Verizon Communications, I could not find corresponding observed data for firm profit. Instead, the observed profit is taken from the data for Verizon Communciations, which offers a wider set of products and services. To correct for it,	Obvious calculation/ General fact

Name of element	Type	Equation/Value	Units	Documentation	Source
				I multiply the total revenue by 1.2, which reflects the average difference between revenues of the two businesses (Verizon Wireless vs. Verizon Communications) over time.	
Reference_Storage_Cost_Per_Data_Unit	Variable	IF (.Scenario_Status_BDA_Explosion+.Scenario_Status_BDA_Winter = 0) THEN (3.351/12) ELSE (IF(.Scenario_Status_BDA_Explosion=1) THEN ((3.351/12)*0.5) ELSE ((3.351/12)*1.5))	USD/GB/Months	The average storage cost that firms have to pay per data unit (used for scenario analysis)	https://blog.storagecraft.com/file-storage-cost-statistics/#:~:text=According%20to%20one%20infographic%2C%20the,average%20of%20%24450%20per%20user.
Total_Costs[Company]	Variable	Actual_Firm_Expenditure_on_Collecting_Extra_Data + Data_Storage_Cost_Per_Month + Market.Actual_Expenditure_in_Direct_Marketing + Investment_Policy.Mass_Marketing_Expenditure	USD/Months	Total monthly costs of the firm including (direct and mass) marketing expenditures as well as costs of data storage and extra data acquisition (array)	Obvious calculation/ General fact
Total_Investments[Company]	Variable	Big_Data_Value.Actual_Investment_in_BDA + Knowledge_Application.Direct_Marketing_Investment + Investment_Policy.Spending_on_Hardware + Investment_Policy.Spending_on_Service + Investment_Policy.Spending_on_Software	USD/Months	Total investments of the firm including investments in BDA, direct marketing, and product quality (hardware, software, and service) (array)	Obvious calculation/ General fact
Total_Operation_Expenses[Company]	Variable	Total_Costs+ Total_Investments	USD/Months	Total expenses the firm must pay each month (array)	Obvious calculation/ General fact
Investment_Policy:					
Fraction_of_Direct_Marketing_Expenditure[Company]	Constant	0.3	Dimensionless	The fraction of total marketing budget planned to spend on direct marketing activities per month, calculated based on the firm's annual reports (array) and own assumption	1) T-Mobile T-Mobile. (2007-2019). Annual Reports & Proxy Statements. Retrieved from https://investor.tmobile.com/financial-performance/annual-reports-and-proxy-statements/default.aspx 2) Verizon Verizon. (2006-2019). Verizon annual reports. Retrieved from: https://www.verizon.com/about/investors/annual-report
Fraction_of_Direct_Marketing_Investment[Company]	Variable	1-Fraction_of_Mass_Marketing_Expenditure - Fraction_of_Direct_Marketing_Expenditure	Dimensionless	The fraction of total marketing budget planned to invest in increasing the quality of direct marketing per month, calculated	1) T-Mobile T-Mobile. (2007-2019). Annual Reports & Proxy Statements.

Name of element	Type	Equation/Value	Units	Documentation	Source
				based on the firm's annual reports (array) and own assumption	Retrieved from https://investor.tmobile.com/financial-performance/annual-reports-and-proxy-statements/default.aspx 2)Verizon Verizon. (2006-2019). Verizon annual reports. Retrieved from: https://www.verizon.com/about/investors/annual-report
Fraction_of_Investment_in_BDA[T_Mobile]	Variable	(1-."Policy_Status_T-Mobile_Reaction_1"-."Policy_Status_T-Mobile_Reaction_2")*0.06+ ."Policy_Status_T-Mobile_Reaction_1"*0.12+ ."Policy_Status_T-Mobile_Reaction_2"*0.3	Dimensionless	The fraction of net revenue planned to use for investment in BDA per month (used for policy analysis)	https://www.mckinsey.com/industries/technology-media-and-telecommunications/our-insights/big-data-getting-a-better-read-on-performance#
Fraction_of_Investment_in_BDA[Verizon]	Variable	(1-.Policy_Status_Verizon)*0.06+ .Policy_Status_Verizon*0.12	Dimensionless	The fraction of net revenue planned to use for investment in BDA per month (used for policy analysis)	https://www.mckinsey.com/industries/technology-media-and-telecommunications/our-insights/big-data-getting-a-better-read-on-performance#
Fraction_of_Investment_in_Data_Acquisition[T_Mobile]	Variable	(1-."Policy_Status_T-Mobile_Reaction_1"-."Policy_Status_T-Mobile_Reaction_2")*0.05+ ."Policy_Status_T-Mobile_Reaction_1"*0.1+ ."Policy_Status_T-Mobile_Reaction_2"*0.25	Dimensionless	The fraction of net revenue planned to use for investment in data acquisition per month (array) (used for policy analysis)	https://www.mckinsey.com/industries/technology-media-and-telecommunications/our-insights/big-data-getting-a-better-read-on-performance#
Fraction_of_Investment_in_Data_Acquisition[Verizon]	Variable	(1-.Policy_Status_Verizon)*0.05+ .Policy_Status_Verizon*0.1	Dimensionless	The fraction of net revenue planned to use for investment in data acquisition per month (array) (used for policy analysis)	https://www.mckinsey.com/industries/technology-media-and-telecommunications/our-insights/big-data-getting-a-better-read-on-performance#
Fraction_of_Investment_in_Hardware[Company]	Constant	0.1	Dimensionless	The fraction of net revenue planned to use for investment in hardware quality per month, calculated based on the firm's annual reports (array)	1) T-Mobile T-Mobile. (2007-2019). Annual Reports & Proxy Statements. Retrieved from

Name of element	Type	Equation/Value	Units	Documentation	Source
					https://investor.tmobile.com/financial-performance/annual-reports-and-proxy-statements/default.aspx 2)Verizon Verizon. (2006-2019). Verizon annual reports. Retrieved from: https://www.verizon.com/about/investors/annual-report
Fraction_of_Investment_in_Service[Company]	Constant	0.25	Dimensionless	The fraction of net revenue planned to use for investment in service quality per month, calculated based on the firm's annual reports (array)	1) T-Mobile T-Mobile. (2007-2019). Annual Reports & Proxy Statements. Retrieved from https://investor.tmobile.com/financial-performance/annual-reports-and-proxy-statements/default.aspx 2)Verizon Verizon. (2006-2019). Verizon annual reports. Retrieved from: https://www.verizon.com/about/investors/annual-report
Fraction_of_Investment_in_Software[Company]	Constant	0.1	Dimensionless	The fraction of net revenue planned to use for investment in software quality per month, calculated based on the firm's annual reports (array)	1) T-Mobile T-Mobile. (2007-2019). Annual Reports & Proxy Statements. Retrieved from https://investor.tmobile.com/financial-performance/annual-reports-and-proxy-statements/default.aspx 2)Verizon Verizon. (2006-2019). Verizon annual reports. Retrieved from: https://www.verizon.co

Name of element	Type	Equation/Value	Units	Documentation	Source
					m/about/investors/annual-report
Fraction_of_Marketing_Expenditure[Company]	Constant	0.2	Dimensionless	The fraction of net revenue planned to spend on (direct and mass) marketing activities per month, calculated based on the firm's annual reports (array)	1) T-Mobile T-Mobile. (2007-2019). Annual Reports & Proxy Statements. Retrieved from https://investor.tmobile.com/financial-performance/annual-reports-and-proxy-statements/default.aspx 2)Verizon Verizon. (2006-2019). Verizon annual reports. Retrieved from: https://www.verizon.com/about/investors/annual-report
Fraction_of_Mass_Marketing_Expenditure[Company]	Constant	0.4	Dimensionless	The fraction of total marketing budget planned to spend on mass marketing activities per month, calculated based on the firm's annual reports (array) and own assumption	1) T-Mobile T-Mobile. (2007-2019). Annual Reports & Proxy Statements. Retrieved from https://investor.tmobile.com/financial-performance/annual-reports-and-proxy-statements/default.aspx 2)Verizon Verizon. (2006-2019). Verizon annual reports. Retrieved from: https://www.verizon.com/about/investors/annual-report
Marketing_Budget[Company]	Variable	Business.Net_Revenue* Fraction_of_Marketing_Expenditure	USD/Months	Total budget per month for marketing activities planned by the firm	Obvious calculation/ General fact
Mass_Marketing_Expenditure[Company]	Variable	Marketing_Budget* Fraction_of_Mass_Marketing_Expenditure	USD/Months	Total budget per month for mass marketing activities planned by the firm	Obvious calculation/ General fact
Planned_Direct_Marketing_Expenditure[Company]	Variable	Marketing_Budget* Fraction_of_Direct_Marketing_Expenditure	USD/Months	Total budget per month for direct marketing activities planned by the firm (array)	Obvious calculation/ General fact
Planned_Investment_in_BDA[Company]	Variable	Business.Net_Revenue* Fraction_of_Investment_in_BDA	USD/Months	Monthly amount of investment in BDA planned by the firm (array)	Obvious calculation/ General fact

Name of element	Type	Equation/Value	Units	Documentation	Source
Planned_Investment_in_Extra_Data_Acquisition[Company]	Variable	Business.Net_Revenue* Fraction_of_Investment_in_Data_Acquisition	USD/Months	Monthly amount of investment in extra data acquisition planned by the firm (array)	Obvious calculation/ General fact
Spending_on_Hardware[Company]	Variable	Business.Net_Revenue*Fraction_of_Investment_in_Hardware	USD/Months	Monthly investment to improve quality of hardware planned by the firm (array)	Obvious calculation/ General fact
Spending_on_Service[Company]	Variable	Business.Net_Revenue* Fraction_of_Investment_in_Service	USD/Months	Monthly investment to improve quality of service planned by the firm (array)	Obvious calculation/ General fact
Spending_on_Software[Company]	Variable	Business.Net_Revenue* Fraction_of_Investment_in_Software	USD/Months	Monthly investment to improve quality of software planned by the firm (array)	Obvious calculation/ General fact
Knowledge_Application:					
Quality_of_Direct_Marketing[Company](t)	Stock	Quality_of_Direct_Marketing[Company](t - dt) + (Increase_in_Quality_of_Direct_Marketing[Company] - Loss_of_Quality_of_Direct_Marketing[Company]) * dt Initial value = 0	Dimensionless	The quality of the firm's direct marketing accumulated over time (array)	Obvious calculation/ General fact
Increase_in_Quality_of_Direct_Marketing[Company]	Inflow	MIN(DELAY3 (Direct_Marketing_Investment*Productivity_of_Investment_in_Direct_Marketing, Time_to_Increase_Quality_of_Direct_Marketing), Quality_of_Direct_Marketing_Gap/Time_to_Increase_Quality_of_Direct_Marketing)	Dimensionless/ Months	It refers to the monthly increase in the quality of direct marketing caused by investment in direct marketing (array)	Obvious calculation/ General fact
Loss_of_Quality_of_Direct_Marketing[Company]	Outflow	Quality_of_Direct_Marketing/Time_to_Loss_Quality_of_Direct_Marketing	Dimensionless/ Months	It refers to the monthly decrease in the quality of direct marketing caused by time (e.g., the obsolescence of knowledge) (array)	Obvious calculation/ General fact
Base_Productivity_Direct_Marketing_Investment	Constant	5.00E-10	1/USD	The maximum productivity of investment in direct marketing in case the firm has maximum knowledge of customers and the quality of direct marketing is minimum.	Assumption/Calibration
Direct_Marketing_Investment[Company]	Variable	Investment_Policy.Marketing_Budget* Investment_Policy.Fraction_of_Direct_Marketing_Investment	USD/ Months	The actual money invested in increasing the quality of direct marketing (array)	Obvious calculation/ General fact
Effect_of_Firm_Knowledge_of_Customer_on_Productivity_of_Direct_Marketing_Expenditure[Company]	Graphical Function	GRAPH(Big_Data_Value.Firm_Knowledge_of_Customers) Points: (0.000, 0.000), (0.100, 0.224), (0.200, 0.404), (0.300, 0.456), (0.400, 0.496), (0.500, 0.504), (0.600, 0.531), (0.700, 0.566), (0.800, 0.654), (0.900, 0.798), (1.000, 1.000)	Dimensionless	A graphical function representing the effect of the firm's knowledge of customers on the productivity of direct marketing expenditure (array)	Assumption/Calibration
Effect_of_Firm_Knowledge_of_Customers_on_Churn_Rate[Company]	Graphical Function	GRAPH(Big_Data_Value.Firm_Knowledge_of_Customers) Points: (0.000, 0.993307149076), (0.100, 0.982013790038), (0.200, 0.952574126822), (0.300, 0.880797077978), (0.400, 0.73105857863), (0.500, 0.500), (0.600, 0.26894142137), (0.700, 0.119202922022), (0.800, 0.0474258731776), (0.900, 0.0179862099621), (1.000, 0.00669285092428)	Dimensionless	A graphical function representing the effect of the firm's knowledge of customers on the rate of churn (array)	Assumption/Calibration
Effect_of_Firm_Knowledge_of_Customers_on_Product_Quality[Company]	Graphical Function	GRAPH(Big_Data_Value.Firm_Knowledge_of_Customers) Points: (0.000, 1.0000), (0.100, 1.1007492735), (0.200, 1.16828353115), (0.300, 1.21355309785), (0.400, 1.24389819588), (0.500, 1.26423912339), (0.600, 1.27787405486), (0.700, 1.28701382275), (0.800, 1.29314039238), (0.900, 1.29724715481), (1.000, 1.3000)	Dimensionless	A graphical function representing the effect of the firm's knowledge of customers on product quality (array)	Assumption/Calibration
Effect_of_Firm_Knowledge_of_Customers_	Graphical Function	GRAPH(Big_Data_Value.Firm_Knowledge_of_Customers) Points: (0.000, 1.000), (0.100, 0.601972749314), (0.200, 0.362371190917), (0.300, 0.218137582068), (0.400, 0.131312880006), (0.500, 0.0790467753978),	Dimensionless	A graphical function representing the effect of the firm's knowledge of	Assumption/Calibration

Name of element	Type	Equation/Value	Units	Documentation	Source
on_Targeting_Error_Rate[Company]		(0.600, 0.0475840047107), (0.700, 0.028644274139), (0.800, 0.0172430724556), (0.900, 0.0103798597327), (1.000, 0.0062483927008)		customers on the targeting error rate (array)	
Effect_of_Quality_of_Direct_Marketing_on_Hit_Rate[Company]	Graphical Function	GRAPH(Quality_of_Direct_Marketing) Points: (0.000, 1.000), (0.0833333333333, 1.161), (0.166666666667, 1.64183276858), (0.250, 2.14574534268), (0.333333333333, 2.9528501566), (0.416666666667, 4.10382895916), (0.500, 5.500), (0.583333333333, 6.89617104084), (0.666666666667, 8.0471498434), (0.750, 8.85425465732), (0.833333333333, 9.35816723142), (0.916666666667, 9.650320064), (1.000, 9.919)	Dimensionless	A graphical function representing the effect of the quality of the firm's direct marketing on the direct marketing hit rate	Assumption/Calibration
Effect_of_Quality_of_Direct_Marketing_on_Productivity_of_Expenditure_of_Direct_Marketing[Company]	Graphical Function	GRAPH(Quality_of_Direct_Marketing) Points: (0.000, 1.000), (0.125, 0.987896573477), (0.250, 0.96794139672), (0.375, 0.93504087234), (0.500, 0.880797077978), (0.625, 0.791364180409), (0.750, 0.643914259888), (0.875, 0.400810439561), (1.000, 0.000)	Dimensionless	A graphical function representing the effect of the quality of direct marketing on the productivity of direct marketing expenditure (array)	Assumption/Calibration
Productivity_of_Investment_in_Direct_Marketing[Company]	Variable	Effect_of_Quality_of_Direct_Marketing_on_Productivity_of_Expenditure_of_Direct_Marketing* Effect_of_Firm_Knowledge_of_Customer_on_Productivity_of_Direct_Marketing_Expenditure* Base_Productivity_Direct_Marketing_Investment	1/USD	It refers to the extent to which the quality of direct marketing increases caused by one dollar of investment in direct marketing (array)	Obvious calculation/ General fact
Quality_of_Direct_Marketing_Gap[Company]	Variable	Quality_of_Direct_Marketing_Goal-Quality_of_Direct_Marketing+Loss_of_Quality_of_Direct_Marketing*DT	Dimensionless	A variable used in the normalization of the quality of direct marketing	Obvious calculation/ General fact
Quality_of_Direct_Marketing_Goal	Constant	1	Dimensionless	A variable used in the normalization of the quality of direct marketing	Obvious calculation/ General fact
Time_to_Increase_Quality_of_Direct_Marketing	Constant	3	Months	The number of months an increase in the quality of direct marketing needs to take effect.	Assumption/Calibration
Time_to_Loss_Quality_of_Direct_Marketing	Constant	12	Months	The number of months until the quality of direct marketing is reduced by one unit	Assumption/Calibration
Market:					
Customers[T_Mobile](t)	Stock	Customers[T_Mobile](t - dt) + (Customer_Acquisition_Due_to_Direct_Marketing[T_Mobile] + Customer_Acquisition_Not_Because_of_Direct_Marketing[T_Mobile] - Customer_Churn[T_Mobile]) * dt	person	Total number of customers (subscribers) (array)	Obvious calculation/ General fact
Customers[Verizon](t)	Stock	Customers[Verizon](t - dt) + (Customer_Acquisition_Due_to_Direct_Marketing[Verizon] + Customer_Acquisition_Not_Because_of_Direct_Marketing[Verizon] - Customer_Churn[Verizon]) * dt	person	Total number of customers (subscribers) (array)	Obvious calculation/ General fact
Potential_Customers(t)	Stock	Potential_Customers(t - dt) + (Lost_Target_Customers[T_Mobile] + Lost_Target_Customers[Verizon] + Customer_Churn[T_Mobile] + Customer_Churn[Verizon] + Increase_in_Potential_Customers - Direct_Marketing_Reach[T_Mobile] - Direct_Marketing_Reach[Verizon] - Customer_Acquisition_Not_Because_of_Direct_Marketing[T_Mobile] - Customer_Acquisition_Not_Because_of_Direct_Marketing[Verizon]) * dt	person	Total number of prospective customers who can potentially become the firms' subscribers (available for both firms)	Obvious calculation/ General fact
Target_Customers_Exposed_to_Direct_Marketing[Company](t)	Stock	Target_Customers_Exposed_to_Direct_Marketing[Company](t - dt) + (Direct_Marketing_Reach[Company] -	person	Accumulated number of target customers who are currently exposed to direct marketing content (array)	Obvious calculation/ General fact

Name of element	Type	Equation/Value	Units	Documentation	Source
		Customer_Acquisition_Due_to_Direct_Marketing[Company] - Lost_Target_Customers[Company]) * dt			
Customer_Acquisition_Due_to_Direct_Marketing[Company]	Flow	(Target_Customers_Exposed_to_Direct_Marketing* (1-Targeting_Error_Rate)+ Target_Customers_Exposed_to_Direct_Marketing*Targeting_Error_Rate* Product_Attractiveness)/ Time_to_Perceived_Product_Attractiveness	persons/Months	Total number of new customers acquired through direct marketing per month (array)	Obvious calculation/ General fact
Customer_Acquisition_Not_Because_of_Direct_Marketing[Company]	Flow	Potential_Customers* (1-Reach_Rate) *Product_Attractiveness/Normal_Time_to_Perceived_Product_Attractiveness	persons/Months	Total number of new customers acquired through other channels than direct marketing per month (e.g., mass marketing, word of mouth) (array)	Obvious calculation/ General fact
Customer_Churn[Company]	Flow	Customers*Churn_Rate	persons/Months	number of customers who stop subscribing to the firm's service per month (array)	Obvious calculation/ General fact
Direct_Marketing_Reach[Company]	Flow	Actual_Targeted_Customers* Direct_Marketing_Hit_Rate	persons/Months	Number of target customers exposed to direct marketing messages (e.g., open emails) per month (array)	Obvious calculation/ General fact
Increase_in_Potential_Customers	Inflow	Inital_Potential_Customers* Potential_Market_Growth_Rate	persons/Months	The number of new potential customers per month	Obvious calculation/ General fact
Lost_Target_Customers[Company]	Flow	Target_Customers_Exposed_to_Direct_Marketing*(1-Purchase_Rate)/Direct_Marketing_Campaign_Running_Time	persons/Months	The number of target customers exposed to direct marketing who decide not to become subscribers per month (array)	Obvious calculation/ General fact
Actual_Expenditure_in_Direct_Marketing[Company]	Variable	MIN(Investment_Policy.Planned_Direct_Marketing_Expenditure, Demand_For_Direct_Marketing_Expenditure)	USD/Months	The actual direct marketing expenditure of the firm per month (array)	Obvious calculation/ General fact
Actual_Targeted_Customers[Company]	Variable	Actual_Expenditure_in_Direct_Marketing/ Average_Cost_of_Direct_Marketing_Per_Customer	person	The number of potential customers actually targeted by the firm (i.e., received direct marketing contacts) (array)	Obvious calculation/ General fact
Average_Cost_of_Direct_Marketing_Per_Customer	Constant	3.07	USD/person/Months	The average monthly delivery cost of the direct marketing message per customer	https://www.wordstream.com/blog/ws/2019/11/12/facebook-ad-benchmarks
Average_Mass_Marketing_Expenditure	Variable	SUM(Investment_Policy.Mass_Marketing_Expenditure)/2	USD/Months	Average mass marketing expenditure per month in the whole market	Obvious calculation/ General fact
Average_Price	Variable	SUM(Price)/2	USD/person/Months	Average subscription fee per customer per month in the market	Obvious calculation/ General fact
Average_Spending_on_Hardware	Variable	SUM(Investment_Policy.Spending_on_Hardware)/2	USD/Months	Average monthly investment to improve quality of hardware in the whole market	Obvious calculation/ General fact
Average_Spending_on_Service_Per_Customer	Variable	SUM(Spending_on_Service_Per_Customer)/2	USD/person/Months	Average monthly investment to improve quality of service per customer in the whole market	Obvious calculation/ General fact
Average_Spending_on_Software	Variable	SUM(Investment_Policy.Spending_on_Software)/2	USD/Months	Average monthly investment to improve quality of software in the whole market	Obvious calculation/ General fact
Churn_Rate[Company]	Variable	SMTH3 (Normal_Churn_Rate* Knowledge_Application.Effect_of_Firm_Knowledge_of_Customers_on_Churn_Rate* (1+Effect_of_Product_Attractiveness_on_Churn_Rate), 3, Normal_Churn_Rate)	Per Months	Actual churn rate which is normal churn rate influenced by the firm's knowledge of customers and product attractiveness	Obvious calculation/ General fact

Name of element	Type	Equation/Value	Units	Documentation	Source
"Customer_Churn_Rate_T-Mobile"	Graphical Function	GRAPH(TIME) Points: (0.00, 0.0), (3.11111111111, 0.0), (6.22222222222, 0.0), (9.33333333333, 0.0), (12.4444444444, 0.0), (15.5555555556, 0.0), (18.6666666667, 0.0), (21.7777777778, 0.0), (24.8888888889, 0.0), (28.00, 0.0), (31.1111111111, 0.0), (34.2222222222, 0.0), (37.3333333333, 0.0), (40.4444444444, 0.0), (43.5555555556, 0.0), (46.6666666667, 0.0), (49.7777777778, 0.0), (52.8888888889, 0.0), (56.00, 0.0), (59.1111111111, 0.0), (62.2222222222, 0.0), (65.3333333333, 0.0), (68.4444444444, 0.0), (71.5555555556, 0.0), (74.6666666667, 0.0), (77.7777777778, 0.0), (80.8888888889, 0.0), (84.00, 0.0)	Per Month	Observed percentage rate at which customers stop subscribing to T-Mobile's service per month	https://www.statista.com/statistics/219793/contract-customer-churn-rate-of-t-mobile-usa-by-quarter/
Customer_Churn_Rate_Verizon	Graphical Function	GRAPH(TIME) Points: (0.00, 0.013), (3.11111111111, 0.0123), (6.22222222222, 0.0128), (9.33333333333, 0.0127), (12.4444444444, 0.0137), (15.5555555556, 0.0125), (18.6666666667, 0.0129), (21.7777777778, 0.0139), (24.8888888889, 0.0133), (28.00, 0.0118), (31.1111111111, 0.0121), (34.2222222222, 0.0123), (37.3333333333, 0.0123), (40.4444444444, 0.0119), (43.5555555556, 0.0128), (46.6666666667, 0.0134), (49.7777777778, 0.0139), (52.8888888889, 0.0118), (56.00, 0.0119), (59.1111111111, 0.0124), (62.2222222222, 0.0128), (65.3333333333, 0.0118), (68.4444444444, 0.0122), (71.5555555556, 0.0124), (74.6666666667, 0.0132), (77.7777777778, 0.0123), (80.8888888889, 0.0127), (84.00, 0.013)	Per Month	Observed percentage rate at which customers stop subscribing to Verizon's service per month	https://www.statista.com/statistics/219805/retail-churn-rate-of-verizon-by-quarter/
Demand_For_Direct_Marketing_Expenditure[Company]	Variable	Potential_Customers* Average_Cost_of_Direct_Marketing_Per_Customer	USD/Months	The desired direct marketing expenditure per month if the firm targets the whole potential market (array)	Obvious calculation/ General fact
Direct_Marketing_Campaign_Running_Time	Constant	6	Months	The number of months in which the firm's direct marketing campaign lasts	https://www.adedgemarketing.com/how-long-should-a-digital-marketing-campaign-last/
Direct_Marketing_Hit_Rate[Company]	Variable	MIN(Reference_Direct_Marketing_Hit_Rate* Knowledge_Application.Effect_of_Quality_of_Direct_Marketing_on_Hit_Rate, 1)	Dimensionless/ Months	The percentage of customers received direct marketing contacts actually expose themselves to the marketing messages per month	Obvious calculation/ General fact
Effect_of_Product_Attractiveness_on_Churn_Rate[Company]	Graphical Funtion	GRAPH(Product_Attractiveness/ Relative_Product_Attractiveness) Points: (0.000, 0.993307149076), (0.100, 0.982013790038), (0.200, 0.952574126822), (0.300, 0.880797077978), (0.400, 0.73105857863), (0.500, 0.500), (0.600, 0.26894142137), (0.700, 0.119202922022), (0.800, 0.0474258731776), (0.900, 0.0179862099621), (1.000, 0.00669285092428)	Dimensionless	A graphical function representing the effect of product attractiveness on the rate of churn	Assumption/Calibration
Effect_of_Word_of_Mouth_on_Product_attractiveness[Company]	Graphical Funtion	GRAPH(Market_Share) Points: (0.0, 1.0000), (14.2857142857, 1.13302092665), (28.5714285714, 1.20814025454), (42.8571428571, 1.25056150031), (57.1428571429, 1.27451754656), (71.4285714286, 1.28804596001), (85.7142857143, 1.29568570024), (100.0, 1.3000)	Dimensionless	A graphical function representing the effect of word of mouth on product attractiveness	Assumption/Calibration
Hardware_Elasticity	Constant	0.47	Dimensionless	The percent change in relative product quality in response to 1% percent change in the relative quality of hardware	Assumption/Calibration
Inital_Potential_Customers	Constant	18000000	persons	Initial number of potential customers adapted from the whole market size for telecommunication sector in US	https://www.statista.com/statistics/283507/subs

Name of element	Type	Equation/Value	Units	Documentation	Source
					cribers-to-top-wireless-carriers-in-the-us/
Initial_Customers[T_Mobile]	Constant	33968000	persons	Initial number of total customers at the beginning of the simulation period (2013) (array)	https://www.statista.com/statistics/219564/total-contract-customers-of-t-mobile-usa-by-quarter/
Initial_Customers[Verizon]	Constant	116750000	persons	Initial number of total customers at the beginning of the simulation period (2013) (array)	https://www.statista.com/statistics/283507/subscribers-to-top-wireless-carriers-in-the-us/
Market_Share[Company]	Variable	100*Customers/ SUM(Customers)	Dimensionless	The fraction of the total customers in the whole market owned by the firm	Obvious calculation/ General fact
Mass_Marketing_elasticity	Constant	0.15	Dimensionless	The percent change in product attractiveness in response to 1% percent change in mass marketing expenditure	Sethuraman, R., Tellis, G. J., & Briesch, R. A. (2011). How well does advertising work? Generalizations from meta-analysis of brand advertising elasticities. Journal of Marketing Research, 48(3), 457-471.
Normal_Churn_Rate[T_Mobile]	Historical data	"Customer_Churn_Rate_T-Mobile"	Per Months	Observed percentage rate at which customers stop subscribing to the firm's service per month (array)	https://www.statista.com/statistics/219793/contract-customer-churn-rate-of-t-mobile-usa-by-quarter/
Normal_Churn_Rate[Verizon]	Historical data	Customer_Churn_Rate_Verizon	Per Months	Observed percentage rate at which customers stop subscribing to the firm's service per month (array	https://www.statista.com/statistics/219805/retail-churn-rate-of-verizon-by-quarter/
Normal_Time_to_Perceived_Product_Attractiveness	Constant	6	Months	Number of months potential customers who are not exposed to direct marketing need to decide whether or not to subscribe on average.	Assumption/Calibration
Potential_Market_Growth_Rate	Constant	0.06	Per Months	The extent at which the potential market is growing, which is calculated based on the growth rates of the firms' customer bases over time	Assumption/Calibration
Price[T_Mobile]	Constant	25	USD/person/Months	Subscription fee per customer per month (array)	https://prepaid.t-mobile.com/prepaid-plans/connect
Price[Verizon]	Constant	55	USD/person/ Months	Subscription fee per customer per month (array)	https://www.verizon.com/plans/5gb-for-55/

Name of element	Type	Equation/Value	Units	Documentation	Source
Price_Elasticity	Constant	-0.7	Dimensionless	The percent change in product attractiveness in response to 1% percent change in price (monthly subscription fee)	O'Donnell, S., & Epstein, L. H. (2019). Smartphones are more reinforcing than food for students. Addictive behaviors, 90, 124-133.
Product_Attractivenes s[Company]	Variable	(Relative_Product_Quality^Product_Quality_Elasticity)* (Relative_Price^Price_Elasticity)* (Relative_Mass_Marketing^Mass_Marketing_elasticity)*Effect_of_Word_of _Mouth_on_Product_attractiveness	Dimensionless	The attractiveness of the firm's product perceived by customers, which is dependent on relative price, relative product quality, and mass marketing expenditure. The formula using elasticity is inspired by the formula 6 in Pierson and Sterman (2013, p. 134)	Pierson, K., & Sterman, J. D. (2013). Cyclical dynamics of airline industry earnings. System Dynamics Review, 29(3), 129-156.
Product_Quality_Elast icity	Constant	0.47	Dimensionless	The percent change in product attractiveness in response to 1% percent change in product quality.	Chenet, P., Dagger, T. S., & O'Sullivan, D. (2010). Service quality, trust, commitment and service differentiation in business relationships. *Journal of services Marketing*.
Purchase_Rate[Compa ny]	Variable	Customer_Acquisition_Due_to_Direct_Marketing*DT/(MAX(Target_Custo mers_Exposed_to_Direct_Marketing, 1))	Dimensionless	The ratio of total number of target customers exposed to direct marketing who decide to become subscribers to the total number of target customers exposed to direct marketing (array)	Obvious calculation/ General fact
Reach_Rate[Company]	Variable	SUM(Direct_Marketing_Reach)*DT/ MAX(Potential_Customers, 1)	Dimensionless	The fraction of total potential customers in the market who are exposed to the firm's direct marketing messages (array)	Obvious calculation/ General fact
Reference_Direct_Mar keting_Hit_Rate	Constant	0.1	Dimensionless/ Months	The percentage of customers received direct marketing contacts would normally expose themselves to the marketing messages per month	https://yourbusiness.azcentral.com/average-success-rate-direct-marketing-21267.html
Reference_Targeting_ Error_Rate	Constant	1	Dimensionless	The maximum error rate in the firm's targeting process (i.e., 100% wrongly targeted)	Assumption/Calibration
Relative_Hardware_sc ore[Company]	Variable	Investment_Policy.Spending_on_Hardware/ Average_Spending_on_Hardware	Dimensionless	Relative quality of hardware computed by comparing the monthly investment to improve quality of hardware by the firm and the average amount of this investment in the whole market (array)	Obvious calculation/ General fact
Relative_Mass_Marke ting[Company]	Variable	Investment_Policy.Mass_Marketing_Expenditure/ Average_Mass_Marketing_Expenditure	Dimensionless	mass marketing expenditure per month by the firm computed relatively to the average mass marketing expenditure in the market (array)	Obvious calculation/ General fact

Name of element	Type	Equation/Value	Units	Documentation	Source
Relative_Price[Company]	Variable	Price/ Average_Price	Dimensionless	subscription fee of the firm computed relatively to the average subscription fee in the market (array)	Obvious calculation/ General fact
Relative_Product_Attractiveness[Company]	Variable	HISTORY(Product_Attractiveness, TIME - 12)	Dimensionless	A variable represents how attractive the firm's product is compared to how it was since 12 months ago	Assumption/Calibration
Relative_Product_Quality[Company]	Variable	(Relative_Service_Score^Service_Elasticity)* (Relative_Hardware_score^Hardware_Elasticity)* (Relative_Software_Score^Software_Elasticity)*Knowledge_Application.Effect_of_Firm_Knowledge_of_Customers_on_Product_Quality	Dimensionless	Quality of the product computed relatively to the average product quality in the market (array)	Obvious calculation/ General fact
Relative_Service_Score[Company]	Variable	Spending_on_Service_Per_Customer/ Average_Spending_on_Service_Per_Customer	Dimensionless	Relative quality of service computed by comparing the monthly investment to improve quality of service per customer by the firm and the average amount of this investment in the whole market (array)	Obvious calculation/ General fact
Relative_Software_Score[Company]	Variable	Investment_Policy.Spending_on_Software/ Average_Spending_on_Software	Dimensionless	Relative quality of hardware computed by comparing the monthly investment to improve quality of software by the firm and the average amount of this investment in the whole market (array)	Obvious calculation/ General fact
Service_Elasticity	Constant	0.47	Dimensionless	The percent change in relative product quality in response to 1% percent change in the relative quality of service	Assumption/Calibration
Software_Elasticity	Constant	0.47	Dimensionless	The percent change in relative product quality in response to 1% percent change in the relative quality of software	Assumption/Calibration
Spending_on_Service_Per_Customer[Company]	Variable	Investment_Policy.Spending_on_Service/ Customers	USD/person/Months	Monthly investment to improve quality of service per customer (array)	Obvious calculation/ General fact
Targeting_Error_Rate[Company]	Variable	Reference_Targeting_Error_Rate*Knowledge_Application.Effect_of_Firm_Knowledge_of_Customers_on_Targeting_Error_Rate	Dimensionless	The actually ratio of potential customers who are wrongly targeted	Obvious calculation/ General fact
Time_to_Perceived_Product_Attractiveness	Constant	3	Months	Number of months potential customers exposed to direct marketing need to decide whether or not to subscribe on average.	Assumption/Calibration

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