DIGITIZATION OF FINANCIAL SERVICES AND FIRM PERFORMANCE

TING CAO

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Abstract

This dissertation focuses on the digitization of financial services in financial institutions (FIs) and investigates *whether* and *how* digitization efforts can help firms improve their performance. We conduct two studies each answering key questions from a different angle.

Study 1 starts with the increasing digital investments of FIs and investigates whether FIs can gain positive returns from their investment in emerging digital technologies. Given the lack of proper tools to measure how well FIs have utilized their digital investments, we propose a new approach using data envelopment analysis to capture returns on investment in digital technologies. Additionally, we adopt a two-stage analysis to further investigate the factors that could potentially improve the returns. Our findings show that FIs have had decreasing returns on investments in digital technologies over time. Particularly, it is the inefficient resource management, rather than the invested technologies themselves, that prevent FIs from realizing the benefits of digital investment. We suggest that it is essential for FIs to continuously assess and monitor the implementation of their digital investments and learn how to optimally deploy technological resources internally. Our study also shows that FIs can gain better performance by actively enhancing their innovation capability and collaborating with FinTech firms.

Study 2 turns to the digitization of existing services that FIs provide to individual customers and examines whether elevating digitization capability would improve performance. We first define a new construct to capture the ability of FIs to actively utilize emerging digital technologies to digitize service offerings. We then propose a new theoretical model in which the drivers and outcomes of building digitization capability are linked together. To empirically test the model, we collect both primary data from a well-designed, web-based survey and secondary data from FI annual reports. We first show that elevating digitization capability is indeed beneficial for FIs to gain better performance. We also show that focusing on digital-savvy customers and aligning the front-office back-office process are two important drivers for FIs in the development of their digitization capability, and these efforts also indirectly help improve performance.

To my loving parents and my husband

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It is not an ending but a new start. Let me quote my favoriate saying from Prof. Cook, "*Keep your foot on the accelerator and get those next papers into the pipeline*".

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Chapter 1

Introduction

Financial institutions (FIs) today are experiencing profound digitization of their financial services, which is fundamentally changing the way of operations and the way of banking (Basole & Patel, 2018). Broadly speaking, the *digitization of financial services* refers to the use of emerging digital technologies (e.g., mobile technology, AI) by FIs to digitize service offerings in order to improve firm performance (see Westerman, Bonnet, & Mcafee, 2014a, for example).

However, not all digitization efforts succeed. Firstly, FIs have wasted a lot of money on digital technologies without knowing whether their investment would pay back (FinancialPost, 2019). Globally, over US$ 1 trillion has been invested by FIs since 2015 to enable technologies such as cloud- and AI-based analytics, but few of them reap the benefits (Accenture, 2019a). More than 43% of investors are even concerned that the increasing digital investments would negatively affect their profitability over time (AmericanBanker, 2020). Yet, because the tools used to measure the return on investment in digital technologies remain lacking, FIs and investors remain in the dark about the difference their investment can make (AmericanBanker, 2020). Secondly, FIs have been experiencing a high failure rate, ranging from 60% to 85% worldwide, when applying digital technologies to their digitization of financial services (Siemens IoT Services, 2019). Common pitfalls include but are not limited to a lack of digitization capability, inadequate understanding of customers, unclear strategies, as well as internal operation challenges (Deloitte, 2020; Deloitte, 2018). Overall, *whether* and *how* the digitization of financial services can actually improve performance remains unclear.

In this dissertation, we focus on the ongoing digitization of financial services in FIs and investigate the impacts of digitization efforts on firm performance. Particularly, two studies are included in this dissertation with each exploring key research questions from a different angle. In Chapter 2, we focus on the digital investment of FIs and answer the first research question: *Does financial institutions' investment in emerging digital technologies pay back?* And in Chapter 3, we focus on the digitization of service offerings and investigate the second research question:

Does financial institutions' capability to digitize financial services improve their business performance?

More specifically, in Chapter 2, "Has Technological Investment Been Worth It? Assessing the Aggregate Efficiency of Nonhomogeneous Bank Holding Companies in the Digital Age," we focus on the bank holding companies (BHCs) in the United States and investigate whether their investment in digital technologies helps improve their performance. Considering the lack of proper tools to evaluate how well BHCs' digital investments have been spent, we propose a new method using data envelopment analysis (DEA) to evaluate the return on investment in digital technologies. We collect panel data from 81 U.S. BHCs from 2010 to 2016. We consider BHCs as profit generators that aim to create greater income (output) from their investments in data-processing-related technologies (input). We use the ratio (i.e., the efficiency score) to reflect the relative return on digital investment in comparison with other BHCs. Particularly, we find that the literature (a) has not explicitly addressed the non-homogeneity issue among BHCs, (b) has not provided practical insights into the re-allocation of shared resources within BHCs, and (c) has not examined explanatory variables that may potentially improve the return on digital investment. As such, we further investigate two follow-up questions: (i) *How to evaluate the return on investment in digital technologies while simultaneously ensuring BHCs are compared to their true peers and allowing technological resources to be allocated into the right places*? And (ii) *What are the impacts of selected key factors on the return of digital investment?* To answer these questions, we adopt Simar and Wilson's (2007) two-stage analysis. Especially, in Stage 1, we develop a new resource-allocation DEA model that addresses the issues of non-homogeneity and allocation of shared resources, and we obtain the aggregate efficiency scores for the BHCs. In Stage 2, we utilize the bootstrapped truncated regression to examine selected factors, including BHC size, innovation capability, diversification, and FinTech collaboration. Our findings show that BHCs have been experiencing decreasing returns on digital investment over time. However, our detailed investigation of efficiency scores components suggests that the decreasing returns are not due to the technology itself but rather the inefficient resource management. We also show that internal efforts (i.e., *innovation capability*) and external efforts (i.e., *collaboration with FinTech firms*) are important in improving the return on digital investments.

In Chapter 3, "Digitizing Retail Banking Services: An Empirical Examination of Drivers and Outcomes of Digitization Capability," we focus on the digitization of retail banking services in retail banks and credit unions (retail banking units, hereafter referred to as "RBUs") in Canada and investigate whether elevating digitization capability can contribute to better performance. Given the inadequate understanding of digitization capability and insufficient empirical examination of its drivers and outcomes (Chen et al., 2019; Holmlund et al., 2017; Liu et al., 2011; Maiya, 2017; Sia et al., 2016), we first define a new construct, *capability to digitize retail banking services*, to reflect the ability of RBUs to integrate and leverage emerging digital technologies to digitize their retail banking services. We then test its drivers and outcomes in our proposed theoretical model. Especially, in this model, marketing-level strategic decisions (i.e., digital-savvy customer focus) and operational efforts (i.e., front-office back-office process alignment) are considered key drivers of digitization capability, and the improvement in business performance (e.g., increase in customer base, market share growth); objective financial performance (i.e., change of ROA and ROE) are considered outcomes of elevating digitization capability. To empirically test our model, we design a web-based survey to collect primary data from 32 retail banks and 92 credit unions in Canada. We also collect secondary data of these RBUs based on their 2020–2021 annual reports. Our findings show that focusing on digital-savvy customers and aligning front-office back-office process are acting as important drivers for RBUs to enhance their capability to digitize retail banking services. Most importantly, we show that elevating the capability to digitize retail banking services helps RBUs improve their performance. Furthermore, our study demonstrates that digitization capability acts as a mediator to explain how strategic and operational efforts are transformed into improved performance.

Chapter 2

Has Technological Investment Been Worth It? Assessing the Aggregate Efficiency of Nonhomogeneous Bank Holding Companies in the Digital Age

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Abstract

Using panel data from 2010 to 2016, this study investigates how well banking institutions perform in investing in digital technologies and utilizing their resources in the digital age. A conventional data envelopment (DEA) analysis model is first applied, followed by a Malmquist index analysis. Results suggest that bank holding companies (BHCs) have failed to benefit from technological progress due to inefficient resource management. As such, we propose a novel resource-allocation model to address the issues, particularly allowing non-homogeneous BHCs to be compared with their true peers and highlighting practical insights into the allocation and reallocation of shared resources. Aggregate efficiency scores are measured and then regressed against selected explanatory variables. The empirical findings indicate that BHCs should strengthen their innovation capabilities and improve their diversification levels to gain better performance in utilizing resources. The results also offer novel managerial implications for collaboration with financial technology (FinTech) firms. Specifically, the explanatory variable, partnership, is shown to have a moderating effect on the relationship between the size and aggregate efficiency of BHCs. Larger BHCs could benefit from collaborating with FinTech, while smaller BHCs appear to be better off acting alone.

Keywords: Data envelopment analysis; Aggregate efficiency; Resource-allocation model; Digitalization in banking

2.1 Introduction

Over the recent years, the banking industry has experienced continuous evolution because of digitalization. Digital technologies are expected to bring profound changes to the way people work (Martínez-Caro et al., 2020), offer possibilities for greater efficiency (Tabrizi et al., 2019), and improve bank performance (Wang et al., 2020). A McKinsey report (2015) estimated that on average, an automated account opening service can dramatically reduce a bank's processing time from two days to 5–10 minutes. A recent Wells Fargo analysis predicted that artificial intelligence (AI) can reduce the mortgage processing cost by 10% to 20% (Financial Times, 2019). The promising benefits of emerging digital technologies have attracted numerous investments worldwide. In the United States alone, banks are spending more than $ 150 billion every year on new technologies, with the possibility of increasing investment even further (Financial Times, 2019).

However, not all banks succeed in technology investment and implementation. It has been estimated that with a $ 1.3 trillion investment in digital transformation in 2018, more than $ 900 billion has been wasted (Tabrizi et al., 2019). Neither banks nor investors know how these investments were spent. Less than 1% of investors believe the bank's digital investments are well planned (AmericanBanker, 2020). A bank CFO once complained that "*I know 50% of my digital transformation spend is wasted — I just don't know which 50%.*" (Bloomberg, 2020). Notably, "*Part of the problem is that banks track their technology investment poorly*," stated in AmericanBanker (2020), "*the tools used to measure the return on investment of digital initiatives are lacking*." Furthermore, studies show that over 70% of digital initiatives did not reach the intended goals (Tabrizi et al., 2019) and more than 50% of banks found it to very challenging to upgrade technologies without disrupting their daily operations (Accenture, 2019b). For many of them, failing to implement technologies properly also reflects a lack of changing mindsets and processes inside of the organization (Martínez-Caro et al., 2020). Essentially, digital transformation is not merely about the technology itself. Analyzing emerging technologies (Porter et al., 2004), managing technological progress (Hekkert et al., 2007), and deploying technology are all critical tasks (Johnston & Clark, 2005; Machuca et al., 2007). The payoff can only start once banks adapt to a new system (Tabrizi et al., 2019). Survival in this digital age may largely depend on how to efficiently place the "right" technologies in the "right" places, as any inefficient players will ultimately be forced out (Parviainen et al., 2017).

Considering such, our study aims to explore whether or not banks' investments in digital technologies have paid back? After a long history of investment, have technologies progressed over time and have banks benefited from them? If not, what are the obstacles? Since there is no tool to assess how well banks' digital investments have been spent, we decide to leverage the data envelopment analysis (DEA) to evaluate the return on digital investment of the banking industry in the United States. DEA technique is widely used for the evaluation of organizational performance (Santos et al., 2018) as well as the analysis of future technology (Porter et al., 2004). The banking industry, as one of the top application fields of DEA, has fuelled a significant amount of attention from researchers (e.g., Emrouznejad & Yang, 2018; Paradi, Rouatt, & Zhu, 2011; Paradi & Zhu, 2012) and practitioners, such as bank executives, investors, and policymakers. Notably, previous DEA studies in banking usually consider employee or operating expense as inputs (e.g., K. Du et al., 2018; Wanke et al., 2016) but lack interest and development on digital-related expense. We, therefore, consider banks' investment in their data processing related technologies as a major input and use total income as a major output. The ratio (i.e., the efficiency score) then reflects the relative return on digital investment in comparison with other banks.

A potential issue raises here: *are banks being compared to their true peers?* The banking institutions in the United States are generally operating under a bank holding company (BHC) system. Since 1999, the Gramm-Leach-Bliley Act has made substantial changes to the regulatory environment and has removed the barriers among banking, insurance, and securities companies. As a result, BHCs can engage in new financial activities such as security underwriting, insurance underwriting, and mutual funds investment. This transformation in the banking industry has led to the rapid growth of BHCs in terms of size, scale, and scope, but at the same time, it has also drawn greater attention to the heterogeneity among BHCs (Avraham et al., 2012). As argued in Copeland (2012), "*…before the deregulation in the 1990s, BHCs were constrained to be fairly homogeneous in their mix of income. For 2001 onward, then, we can interpret differences among BHCs in their reliance on securitization and nontraditional income…*" (p. 87). Thus, one way to demonstrate the non-homogeneous nature among banks is based on their income-generating strategy, e.g., whether or not a BHC gets involved in traditional banking (e.g., loan and deposit), securitization, and/or non-traditional (e.g., investment and insurance) (Copeland, 2012). Addressing such non-homogeneous issues is critical for banks to gain a clear view of how well they perform with respect to their true peers; however, a review of relevant banking DEA applications reveals that such non-homogeneous problems have not been fully addressed yet.

Additionally, since technologies enable value creation by introducing new ways of working (Martínez-Caro et al., 2020), the corresponding return may vary across different banking activities. For example, big data can be used for loan processing to collect additional information

(Agarwal & Ben-David, 2018), for retail banking services to generate customized content (Lehrer et al., 2018), for investment banking to improve risk management (Lin et al., 2020). However, banks usually do not provide details on how their digital technologies and relevant investment are being allocated internally. These inspire us to explore a follow-up question: *how to evaluate banks' return on investment of digital while simultaneously ensuring banks are compared to their true peers and allowing digital technologies to be allocated optimally to the "right" places*?

To answer these, we leverage panel data of 81 non-homogeneous BHCs from 2010 to 2016 and conduct the conventional DEA model and the Malmquist index analysis first. We illustrate that, although technologies progressed over time, BHCs still failed to reap the benefit from digital investment because they experienced inefficient resource management internally (both human and digital resources); thus, emphasizing the need to optimize resources (K. Du et al., 2018; Fernandes et al., 2018). Since there is no tool to properly evaluate how well digital investments have been spent and allocated internally, we then develop a new resource-allocation DEA model, in which we allow BHCs to allocate their invested technologies internally into each of the income-generating substreams and then obtain an aggregate evaluation, and at the same time, ensure non-homogeneous BHCs are compared to their true peers.

Finally, after evaluating the aggregate efficiencies of BHCs, this study further investigates the underlying explanatory variables that may potentially help banks to improve the return from digital investment in the digital age. In particular, we leverage the literature on the resource-based view (RBV), innovation management, buyer–supplier relationships (BSRs), and diversification to justify the relationships between explanatory variables and BHC efficiency performance. We then adopt Simar and Wilson's (2007) bootstrapped truncated regression approach to examine the impacts of various factors including BHC size, innovation capability, partnership with technology firms, and BHC diversification. The empirical results suggest that larger size, greater diversification level, and stronger innovation capability are associated with higher aggregate efficiency scores. Regarding the partnership with technology firms, the results show a moderating effect on the relationship between BHC size and aggregate efficiency. Specifically, larger BHCs can gain benefits from collaborating with technology firms, whereas small BHCs are better off acting alone.

The contribution of this study is multi-fold. From a theoretical viewpoint, this is the first study to demonstrate and address the existing non-homogeneous concerns in the banking industry via the lens of BHC's income. Instead of deriving efficiency by taking "total income" as an overall output, our model enables a comparison among non-homogeneous BHCs based on their income-generating strategies. Our innovative model also enables one to assess the allocation and reallocation of resources within a BHC. The analysis of explanatory variables also contributes to the relevant literature streams by either supporting or supplementing previous empirical results. Notably, the findings regarding partnerships indicate that collaborating with financial technology (FinTech) firms can benefit BHCs, but only for the large ones. As such, the finding offers insights for existing and future bank–FinTech collaboration in the digital age. From a practical perspective, our findings show that even though technologies may bring possibilities for greater efficiency, banks may fail to reap the benefits if they do not update their processes and practices accordingly. Our study suggests that both BHCs and policymakers should pay attention to resource management, especially when generating long-term expansion strategies and deregulation policies.

The remainder of this paper is structured as follows. Section 2 discusses DEA methodology- and application-related literature and the selected explanatory variables literature. Section 3 describes the data and variables used in this study. Section 4 covers details of the research methodology, including the conventional DEA model, Malmquist index analysis, resource-allocation model, and bootstrapped truncated regression. Section 5 discusses the detailed results and Section 6 summarizes the relevant theoretical and managerial contributions and implications. Finally, Section 7 presents the concluding remarks.

2.2 Literature Review

2.2.1 Data envelopment analysis applications in the banking industry

DEA is a non-parametric linear programming technique that has been widely adopted for the evaluation of organizations' performance and development of best-practice frontiers. DEA measures the relative efficiency of a set of DMUs with multiple inputs and outputs (Charnes et al., 1978).

The banking industry is so essential to the entire economy that performance evaluation of this sector has been an area of major research interest. Early studies have tended to target the performance of bank branches (e.g., Cook et al., 2000; Cook & Hababou, 2001; Paradi & Schaffnit, 2004). Since the 1990s, a growing number of studies have been conducted to investigate a broader level of bank efficiency from both theoretical development and application aspects (e.g., Wanke et al., 2016), which contribute significantly to assessing performance, examining benchmarks, and assisting policy regulations. A review of relevant DEA studies in the banking industry is summarized in *Appendix 1.1* of *Supplementary Materials*.

The selection of inputs and outputs generally follows the relevant approach (Fethi & Pasiouras, 2010). Three common approaches are usually applied, namely, the production, intermediation, and profitability approaches, which differ by how the DMUs are viewed. For instance, studies considering banks as intermediaries between savers and borrowers would use the intermediation approach with deposits as the input and loans as the output. Other studies that treat banks as profit generators would adopt the profitability approach and consider total income or profit as the output and cost-related variables (such as labor cost, operating cost, etc.) as the input.

Previous studies in the banking industry tend to be more output-oriented rather than input-oriented because banks are treated as output maximizers, while the bank's management team has limited control over inputs. However, the choice of output- vs. input-oriented approaches should be consistent with the research objective. An input-oriented approach is recommended when the study assumes that the bank's management team would have greater control over inputs (resources) than outputs (outcomes), and explores how resource management would make a difference (Fethi & Pasiouras, 2010).

In the study, "*Data Envelopment Analysis-Thirty Years On,*" Cook and Seiford (2009) review progress in the field from both methodological and application perspectives. A large number of DEA models have been developed to reflect variations in methodological assumptions, environmental situations, policy restrictions, and so on. The authors emphasize the importance of developing new models to adapt to new application requirements, especially those that have been overlooked. One of the major shortcomings of many DEA applications is that they often involve a "*comparison of apples with oranges*" especially when such studies fail to consider the non-homogeneous nature among DMUs, including heterogeneous internal structures, operating environments, and even the inputs/outputs being used (Coelli et al., 2005; Fethi & Pasiouras, 2010).

The heterogeneity issue has been well documented in banking studies. Copeland (2012) describes heterogeneity from the perspective of the different income strategies that BHCs pursue. Copeland (2012) groups a BHC's income into the following three streams: (1) traditional income, (2) securitization income, and (3) non-traditional income. Not all BHCs are involved in all three income-generating activities. Some BHCs are more diverse and are involved in all three income-generating activities, while the less diverse BHCs tend to specialize in one- or two-income streams. This taxonomy illustrates how BHCs differ from one another through the view of income, thereby highlighting the question: how should BHCs be benchmarked against their true peers?

Several existing DEA studies have offered insights into non-homogeneity concerns. For example, Cook et al. (2000) propose a method to simultaneously evaluate different components of DMUs by structuring and optimizing aggregate efficiency instead of using one single efficiency measure. Subsequently, Cook and Hababou (2001) introduce and apply a modified additive model to assess the performance of different service components (i.e., sales and service) in bank operations. This aggregate measure of multiple components is useful in identifying a bank's strengths and weaknesses. Their approach also draws attention to the allocation of shared resources among the different subunits. Cook et al. (2012) discuss a situation in which a subset of DMUs has "zero" in some outputs. This situation occurs when DMUs are present in the same industry but produce different outputs. The authors consider this "missing output" situation as a non-homogeneous problem, which, in our case, applies to BHCs with "zero" output in one or two income-generating activities. In another study, Cook et al. (2013) demonstrate how to apply a three-step approach to measure the aggregate efficiency of non-homogeneous DMUs by grouping them into subunits and evaluating all subunits simultaneously.

The three-step approach (Cook et al., 2013) can capture the non-homogeneous nature among BHCs; however, the remaining challenge is, how to assign resources to each subunit when resources are originally tied to the organizational level. It is noteworthy that conventional DEA studies usually measure DMUs' efficiencies while ignoring the allocation of internal resources (inputs), and assume all inputs impact all outputs with unknown proportions. However, this assumption does not apply to heterogeneous DMUs, especially in the case of BHCs when different subunits are responsible for their own income streams. Therefore, knowing how to allocate resources among different subunits (i.e., income-generating activities) becomes vital. Imanirad, Cook and Zhu (2013) adopt the three-step approach (Cook et al., 2013) to measure efficiency when a set of DMUs appear in the form of partial input-output bundles. They propose an intuitive approach of combining the different proportions of shared inputs into input bundles such that each input bundle is assigned to one output bundle per subunit. By combining the idea of a shared partial input-output bundle framework and aggregate scores, a model is developed that allows one to evaluate non-homogeneous BHCs relative to their true peers and simultaneously investigate the resource distribution within each BHC.

2.2.2 Potential explanatory variables

To investigate the factors that potentially affect efficiency performance, different methods that allow researchers to employ statistical models as a follow-up (second stage) analysis have been developed. For instance, early studies use Tobit regression to explore the effect of explanatory factors on efficiency scores. Simar and Wilson (2007) develop a two-stage approach in which DEA analysis is conducted in the first stage and bootstrapped truncated regression is applied in the second stage. Bădin et al. (2010) introduce the conditional efficiency approach by taking both the production process and environmental variables into consideration. Banker et al. (2019) argue that the DEA plus ordinary least square (OLS) approach is also appropriate. Despite the ongoing debate on the advantages and drawbacks of different approaches (Banker et al., 2019), the key to conducting a second stage empirical analysis is to investigate the underlying relationships, which either support or refute the relevant understanding. In this study, since the aggregate efficiency scores are obtained from an externally estimated model, Simar and Wilson's (2007) bootstrapped truncated regression (algorithm 1 approach) is the most appropriate approach to analyze the effects of selected explanatory factors. We, therefore, use the bootstrapped truncated regression in the second stage analysis. Other than that, we also conduct several robustness checks to confirm the consistency of our findings.

In our study, we select explanatory variables based on existing literature. Size, according to previous studies, is always a focal interest but leads to contradictory results. Some studies show that larger banks tend to be associated with higher efficiencies (Chronopoulos et al., 2011; Drake & Howcroft, 2002; Miller & Noulas, 1996; Paradi et al., 2011). However, other studies, Elyasiani and Wang (2012) for instance, show that a larger size generally points to the need for more resources, but at the same time brings greater difficulties in both intra-organizational operations and inter-organizational cooperation. In this study, we examine whether size matters when BHCs are compared with true peers.

A BHC's innovation capability can be critical in driving performance, especially in the digital age. "Often, new technologies can fail to improve organizational productivity because intimate insider knowledge has been overlooked" (Tabrizi et al., 2019). For service organizations, technology adoption and deployment are vital when developing new services and building competitive advantages (Johnston & Clark, 2005; Machuca et al., 2007). Under the RBV, firms can be treated as having a combination of resources, including tangible and intangible assets. Intangible resources are more likely to build competitive advantages due to their rare and imitable characteristics (Barney, 1991). Innovation capability is about the ability to continuously transform knowledge into new products, services, processes, and systems, and it is argued as being composed of various elements such as knowledge, competence-base, organizational intelligence, advanced technology, expertise, and so on (Lawson & Samson, 2002; Romijn & Albaladejo, 2002). From a firm's perspective, such elements (patents, intellectual property, trademarks, etc.) are usually considered intangible assets. Despite important insights regarding the banking industry, previous studies have not yet properly measured and examined the effect of BHC's innovation capability. This backdrop has inspired us to investigate whether innovation capability plays a role in boosting BHC efficiency.

Gradual deregulation has enabled BHCs to engage in broader financial activities, hence leading to a greater level of diversification. Yet, little work has been done to study whether a diversification or a specialization strategy makes banks more efficient. Curi et al. (2015) show that the impact of diversification can be contradictory. On the one hand, BHCs that are more diversified are more likely to be efficient (Chronopoulos et al., 2011) because they have more sources to raise capital, borrow money, issue stock, merge and acquire, among others. On the other hand, increasing diversification also leads to greater complexity and thus, places pressure on efficient management by BHCs (Chernobai et al., 2018; Avraham et al., 2012). As such, our study addresses these points by examining the effect of diversification on BHC efficiency.

FinTech and bank–FinTech relationship are trending topics and managerial concerns in the banking industry (Chang et al., 2020; Drasch et al., 2018; Gomber et al., 2017), but it has not been fully examined in the banking literature. BHCs are motivated to collaborate with FinTech due to the likelihood of improving operational outcomes (Autry & Golicic, 2010). However, the BSRs literature shows conflicting findings when examining the impacts of collaboration on firm performance (Ho et al., 2019). Particularly, studies show that the existence of a partnership does not necessarily bring direct benefits to the focal firm due to potential collaboration challenges (Sanders, 2007). Despite growing research interest and the expanding literature on BSRs in supply chain settings, no enough works have been done to examine the relationship between banks and FinTech firms in a service context. The impact of a bank–FinTech collaboration is still unclear. Hence, in this study, we examine whether BHCs would gain benefits from partnering with technology firms. Furthermore, Ho et al. (2019) argue that implementing supply chain collaboration is a never-ending process that requires ongoing efforts and capabilities from both parties. Considering this, a follow-up question is: Would BHCs with different sizes or different diversification levels hold different collaboration strategies? Since larger BHCs are more likely to have easy access to resources, better-organized systems, more dedicated collaboration teams, and so on, a bank–FinTech collaboration may lead to better performance. Similarly, more diversified BHCs may tend to have greater complexity and require more extensive collaboration efforts and thus, experience difficulties in a bank–FinTech collaboration.

2.3 Data and Variables

This study uses panel data from 81 BHCs from 2010 to 2016. The data were obtained from COMPUSTAT, which covers Federal Reserve data such as FR Y-9C reports. Based on the Bank Holding Company Performance Report from the National Information Center (NIC), BHCs are categorized into peer groups according to their consolidated assets. This peer group categorization is determined by the Federal Reserve Board's Division of Banking Supervision and Regulation. In this study, three peer groups (Peers 1 to 3 from largest to smallest) are identified based on data from 2016. We follow Copeland's (2012) income categorization as presented in Appendix 1.2 of Supplementary Materials, to calculate each income stream first and later add them all up as total income. Table 2.1 summarizes the variables used in the DEA model, including two inputs, one output (total income), and three separate income streams. Table 2.2 shows the descriptive statistics for selected explanatory variables. Finally, the annual reports (10-K) of all BHCs from 2010 to 2016 period were used for further analysis.

Regarding the selection of input variables, employee expense is widely used in DEA models to account for labor input. With the increasing number of digital tools used in BHCs, it is argued that technologies will replace much of human work. Some banks act as digital beginners with limited digital technologies integrated into their products, services and/or systems, whereas other banks may have already become digital masters with the development of relevant digital capabilities to improve overall performance (Westerman, Bonnet, & McAfee, 2014). In this study, we include BHC's expense on technologies, especially on the data processing technologies and activities, as a major resource along with the labor input. Thus, the goal is to determine the optimal allocation of these resources.

Table 2.1: Summary statistics for the outputs and inputs

Outputs	Mean	Std	Min	Max
1. Traditional Income	2653.00	8765.00	20.21	53850.00
2. Securitization Income	324.13	1342.00	0.16	13630.00
3. Non-traditional Income	638.65	3018.00	0.00	22720.00
Total Income (the sum of all three income streams)	3615.00	12780.00	23.24	84620.00
Inputs				
1. Labor expense	1499.00	5612.00	8.31	36970.00
2. Technology expense	141.24	602.37	0.29	5520.00

All numbers are in millions of dollars. The categorization of incomes can be found in Appendix 1.2, which follows Copeland (2012). Employee expense is measured using employee salary and technology expense is measured using data processing related expenses.

Table 2.2: Summary statistics of the explanatory variables

Variables	Description and measures	Mean	Std	Min	Max
Peer group	Peer group is categorized based on the year of 2016 peer performance report (Peer 1, Peer 2, and Peer 3)	1.84	0.81	1.00	3.00
Innovation capability	Innovation capability is measured using a BHC's intangible assets divided by the number of employees	16.41	15.39	0.08	97.91
Partnership	Partnership with technology firms is a dummy variable (=1, if a BHC has	0.54	0.50	0.00	1.00

	partnership with technology firms; =0, otherwise)				
Diversification	(Income) Diversification is a dummy variable (=1, if a BHC gets involved in all three income-generating activities; =0, otherwise)	0.89	0.31	0.00	1.00
NPL	Non-performing loans (NPL) ratio	0.01	0.01	0.00	0.08
Capital adequacy	Capital asset (CAR) ratio	0.11	0.02	0.06	0.30
Year dummies	Year dummy variables	2010, 2011, 2012, 2013, 2014, 2015, 2016			

The measurement of size varies in different studies, such as the natural logarithm of the bank's total assets, the natural logarithm of the bank's total income, and so on. (Chronopoulos et al., 2011; Drake & Howcroft, 2002; Miller and Noulas, 1996; Paradi et al., 2011). This study employs peer group, which is public information released from the NIC, to measure the size of a BHC. BHCs in peer group 1 have larger consolidated assets than the others.

To measure the innovation capability, we use the ratio of intangible assets to the number of employees as a proxy. Previous innovation studies tend to focus on product settings but have overlooked service-oriented innovation (Droege et al., 2009). In contrast to manufacturing products, banking services are generally intangible, thus making the innovation process and competence difficult to quantify. Under the RBV, for BHCs to maintain sustainable competitive advantage, they have to rely heavily on "unique" resources (Barney, 1991). Given that our study uses secondary data, such unique resources can be identified from BHC's intangible assets, which cover patents, intellectual property, trademarks, and so on. Particularly, considering that this study also included size as the explanatory variable, we used the ratio of intangible assets to the number of employees as the proxy to rule out the possibility of multicollinearity.

To measure the bank–FinTech partnership, we conduct a thematic analysis using the BHCs' annual reports (10-K) and transform the extracted information into a binary variable, *partnership*, which equals to 1 if a partnership with technology firms is identified and 0 otherwise. The detailed method is summarized in *Appendix 1.3* of Supplementary Materials.

To measure the diversification, we use a BHC's income-generating stream as a proxy for income diversification. A binary variable is used to capture diversification where the variable is set to 1 if a BHC operates in all three income-generating (traditional, securitization, and non-traditional) activities and 0 otherwise. Previous studies have discussed a variety of ways to measure bank diversification, for example, using asset diversification, funding diversification, and income diversification (Curi et al., 2015). Particularly, Chronopoulos et al. (2011) suggest using the income diversity index to measure a bank's diversification level between interest and non-interest income. In our case, since the income structures among BHCs are distinct, we focus on income diversification and investigate whether BHCs benefit from a diversification strategy (i.e., getting involved in all income-generating activities) or a specialization strategy (i.e., focusing on one or two income-generating activities).

Finally, to account for potential variations from BHC-level characteristics and heterogeneity in the environment and regulations, our study includes a BHC's non-performing loans (NPL) ratio, capital adequacy ratio (CAR), and year dummies as control variables. Previous studies have found that NPL has a strong impact on bank failures (Paradi & Zhu, 2012). The NPL ratio reflects a bank's ability to continue operations and its ability to maintain a healthy financial situation (Elyasiani & Zhang, 2015). Capital adequacy represents the freedom to make decisions in terms of capital and the financial strength to ensure stability (Bhattacharyya et al., 1997). Considering that the goal of this study is to measure aggregate efficiency in allocating resources, financial risk and capital requirements are controlled to exclude any potential impacts on a BHC's operations (Bhattacharyya et al., 1997; Chortareas et al., 2012; Paradi & Zhu, 2012).

2.4 Methodology

In this section, we first present a conventional DEA model. Then, a Malmquist index analysis is conducted to explore productivity changes over time. Following this, we measure the aggregate efficiency of BHCs by introducing a novel resource-allocation model that simultaneously considers the nature of non-homogeneous BHCs and the allocation of shared resources. Finally, we conduct bootstrapped truncated regressions, as a second stage analysis, to examine the impacts of selected explanatory variables on aggregate efficiency scores of BHCs.

2.4.1 A conventional data envelopment analysis model and the Malmquist index

To begin, we follow the approach used in previous DEA studies and conduct an output-oriented conventional DEA analysis by assuming BHCs have limited controls over resources. To minimize the influence of the "curse of dimensionality", the total income of a BHC is used here as a single output (Chowdhury & Zelenyuk, 2016; K. Du et al., 2018). The following model (Banker et al., 1984) used here assumes a variable returns to scale (VRS) technology to allow for increasing, constant and decreasing returns to scale.

$$\boldsymbol{min\ \sum_i v_i x_{i_0} + v_0} \qquad \text{(Eq. 2.1)}$$

subject to

$$\boldsymbol{\sum_i v_i x_{ij} - \sum_r u_r\, y_{rj} + v_0\ \geq 0} \qquad \text{(Eq. 2.2)}$$

$$\boldsymbol{\sum_r u_r\, y_{r_0} = 1} \qquad \text{(Eq. 2.3)}$$

$\boldsymbol{u_r}, \boldsymbol{v_i} \geq \mathbf{0}$ and $\boldsymbol{v_0}$ free in sign (Eq. 2.4)

where (i, r, j) are the indexes on (inputs, outputs, DMUs); v_i and u_r are the decision variables, which are used as multipliers to denote the weights to be assigned to x_{ij}, the inputs, and y_{rj}, the outputs, respectively. The output-oriented conventional DEA model estimates the inefficiency level of BHCs, that is, scores are equal to or greater than 1, where 1 indicates that the DMU in question lies on the efficient frontier.

Regarding whether the constant returns to scale (CRS) or the VRS methodology should be applied in the current setting, it warrants pointing out that there is no simple test one can perform to address this question. Under a CRS *production possibility set* (PPS) it is assumed that if a given DMU(x,y) is in that set, then any positive scaled version k(x,y) of that DMU will also be in the set. The VRS technology does not, however, possess this property. Moreover, the proportionality property of the CRS applies only to the *frontier* DMUs. For inefficient DMUs (those not on the frontier), a definitive statement cannot generally be made as to whether the CRS or VRS property holds for those units. In some situations where the DMUs can go from very small to very large in size, the VRS technology can often provide a more realistic *envelopment* of the data, particularly at the extremes of the input set (e.g., very low values near the origin and very high values at the other end.) The Charnes, Cooper, and Rhodes (CCR) model (Charnes et al., 1978) is simply a ratio of aggregate outputs to aggregate inputs and does not directly display the property regarding the proportionality of outputs to inputs. Only the envelopment CCR model carries such an assumption. From an engineering viewpoint, CRS and VRS models create different shapes of the best-practice frontier. The VRS model generally produces different results compared with those of the CRS model and generates a "tighter" envelopment of the data as mentioned above. The efficiency scores of DMUs tend to be more “generous” under the VRS model than under the CRS model. In the application discussed herein, where DMUs do indeed appear in a wide range of sizes, we have chosen to adopt the VRS technology.

The conventional DEA model offers preliminary results on BHC efficiency. To explore changes over time, we conduct a Malmquist index analysis, which is the desired technique for panel data and can be used to understand how DMUs gain productivity via decompositions over time (Paradi et al., 2011). The findings supplement the results obtained from the conventional DEA model by showing movements over time. Under the current environment, emerging technologies tend to be open to the entire banking industry; thus, in this study, we assume the rate of technological advancement is the same across all DMUs at any given time *t*. A shift in the production frontier from *t* to *t+1* might be explained by the following two perspectives: (1) the overall technological progress that occurs, for instance, new digital services or advanced analytical tools are innovated and employed, and (2) the utilization of resources due to certain efforts, that is, a BHC's optimization of its resource allocation.

In the model below, two periods, t and $t+1$, are considered. Let $x \in \mathbb{R}_+^N$ and $y \in \mathbb{R}_+^M$ denote the input and output vectors. For each period, the production possibility set $\wp^t$ models the transformation of inputs into outputs, specifically:

$$\boldsymbol{\wp^t = \{(x, y) |\ x\ can\ produce\ y\},\ \ t = 1, \dots, T} \qquad \text{(Eq. 2.5)}$$

The output distance function for period t can be stated as

$$\boldsymbol{D_o^t(x^t, y^t) = inf\ \{\theta: (x^t, y^t/\theta) \in \wp^t\}, t = 1, \dots, T.} \qquad \text{(Eq. 2.6)}$$

The Malmquist index is then the geometric mean of two indexes for time periods t and t+1, respectively, as shown in Eq. 2.7.

$$\boldsymbol{M\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = \left\{\frac{D^t\ (x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} * \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)}\right\}^{\frac{1}{2}}} \qquad \text{(Eq. 2.7)}$$

Färe et al. (1994) present the initial decomposition of the Malmquist index as the product of efficiency change and technological change.

$$\boldsymbol{M\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = \left\{\frac{D^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D^t\ (x^t, y^t)}\right\} * \left\{\frac{D^t\left(x^{t+1}, y^{t+1}\right)}{D^{t+1}\ (x^{t+1}, y^{t+1})} * \frac{D^t\ (x^t, y^t)}{D^{t+1}\ (x^t, y^t)}\right\}^{\frac{1}{2}}}$$

$$\boldsymbol{= EFFCH * TECHCH} \qquad \text{(Eq. 2.8)}$$

In the output-oriented model, $M(x^t, y^t, x^{t+1}, y^{t+1})$ measures the productivity change or growth. A value greater than 1 implies an improvement in productivity. The first component, $EFFCH$, measures the relative efficiency change from time t and time t+1 and indicates a movement towards the frontier if the value is greater than 1. The second component, $TECHCH$, captures the movement of technology between two periods and suggests technological improvements and innovations when the value is more than 1. Particularly, when an $EFFCH$ shows a value greater than 1, it can be considered as an improvement effort done to the equally efficient allocation of resources between two time periods, whereas a value less than 1 may suggest potential problems in resource optimization over time since resources are not allocated equally in an efficient manner.

We acknowledge the existence of different decomposition strategies (e.g., Simar & Wilson, 1998). However, criticism also exists, especially on different interpretations against these decomposition strategies. In this study, we do not identify the causes nor interpret the variations in different decomposition strategies. What we need from the Malmquist index and decomposition is an intuitive result that can push BHCs to review their productivity, efficiency, and technological changes over time, and identify any overlooked operational issues that may exist. Therefore, the Färe et al. (1994) decomposition strategy is employed herein because it suits the goal.

2.4.2 Resource-allocation model for nonhomogeneous decision-making units

Chami et al. (2017) explain how BHCs behave differently from banks, and Copeland (2012) shows how to distinguish non-homogeneous BHCs based on their income-generating structures. Fig. 1 below briefly demonstrates a simple situation in which the non-homogeneous BHCs are grouped into two sets (N_p where p=1, 2), N_1 and N_2, based on their income structures. (i, r, j) are the indices on (inputs, outputs, DMU) respectively. As shown in Fig. 1, not all BHCs are the same: some BHCs engage in all traditional, securitization, and non-traditional banking activities while some BHCs engage in only traditional and securitization. As such, a benchmarking based on merely the size of BHCs is not helpful to identify the best practice because BHCs are not compared to their true peers. The "*true*" peers, in this case, should be the ones that are operating under the same income-generating structures. As shown in Fig. 1, BHCs in N_1 represents a particular BHC peer that each BHC engages in all three income-generating activities, whereas those in N_2 represent another type of BHC peer such that each one is involved only in traditional banking activities and securitization.

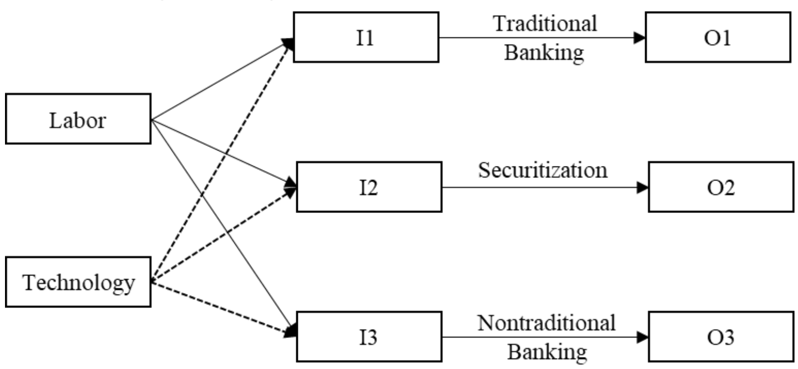
To evaluate the performance of the non-homogeneous BHCs shown in Figure. 2.1, an aggregate efficiency score that combines different income-generating activities is more appropriate than a single efficiency score. Therefore, we adopt the internal income-generating structure from Copeland (2012), in which BHCs' total income is the sum of incomes from traditional banking, securitization, and non-traditional banking activities. Each income-generating activity is defined as a separate subunit; thus, three subunits are included in this model. Figure. 2.2 displays a model that considers internal income-generating structures and shared resources across subunits. Notably, in this study, we focus on the allocation of two selected resources: labor and technology. Our goal is not only to propose a method to properly measure the return on investment of digital but also to provide insights on how to optimally (re)allocate relevant resources (labor and technology) to the "*right*" places (i.e., income-generating activities). As such, an input-oriented setting would seem to be more appropriate since it considers and emphasizes the importance of better control of resources by the BHCs.

Figure 2.1: Non-homogeneous bank holding companies grouped based on income structures

		Outputs		
		Y_1	Y_2	Y_3
	DMU	Traditional income	Securitization Income	Non-traditional Income
N_1	j_1	Y_{1j1}	Y_{2j1}	Y_{3j1}
	j_2	Y_{1j2}	Y_{2j2}	Y_{3j2}
	j_3	Y_{1j3}	Y_{2j3}	Y_{3j3}
	…			
N_2	j'_1	Y'_{1j1}	Y'_{2j1}	-
	j'_2	Y'_{1j2}	Y'_{2j2}	-
	j'_3	Y'_{1j3}	Y'_{2j3}	-
	…			
		Subunit 1 (K=1)	Subunit 2 (K=2)	Subunit 3 (K=3)

Note: (r, j) are the indices on (outputs, DMU)

Figure 2.2: The resource-allocation model for bank holding companies with three income-generating activities and shared resources



Let L_{N_p} represent the group such that for each DMU $j_0 \in N_p$ (where p=1, 2), two resources (labor and technology) are shared among the subunits in proportions $\alpha_{iR_K N_p}$, where i refers to the input, R_k to the subunit, and N_p to the group number. The rationale for using the three-step approach is to enable resources to be split across subunits and gain the aggregate efficiency of a DMU by computing the weighted average of the efficiencies of all subunits of that DMU (Cook et al., 2012, 2013). The steps performed to obtain the resource splits $\alpha_{iR_K N_p}$, subunit weights $W_{R_K j_0}$, subunit efficiencies e_{R_K}, and the aggregate efficiencies are summarized as follows.

Step 1: Deriving the split (proportion $\alpha_{iR_K N_p}$) of inputs

The model follows the VRS methodology by including a free of sign variable u_k^0 for each subunit and setting the input-oriented aggregate efficiency objective as described below. For any DMU $j_0 \in L_{N_{p0}}$,

$$\boldsymbol{e_{agg} = max \sum_{R_K \in L_{N_{p0}}} W_{R_K j_0} \left[\sum_{r \in R_K} (u_r y_{rj_0} + u_k^0) / \sum_{i \in I_K} v_i \alpha_{iR_K N_p} x_{ij_0} \right]} \quad \text{(Eq. 2.9)}$$

subject to

$$\sum_{R_K \in L_{N_{p0}}} W_{R_K j_0} \left[\sum_{r \in R_K} (u_r y_{rj_0} + u_k^0) / \sum_{i \in I_K} v_i \alpha_{iR_k p^0} x_{ij_0}\right] \leq 1 \; \forall j \in N_P, R_K \in L_{N_P}, p = 1..P \quad \text{(Eq. 2.10)}$$

$$\sum_{r \in R_K} u_r y_{rj_0} - \sum_{i \in I_K} v_i \alpha_{iR_k p^0} x_{ij_0} + u_k^0 \leq 0 \; \forall j \in N_{P^0}, R_K \in L_{N_P}, p = 1, \dots, P \quad \text{(Eq. 2.11)}$$

$$\sum_{R_K \in L_{N_P}} \alpha_{iR_K N_p} = 1 \; \forall i, p = 1, \dots, P \quad \text{(Eq. 2.12)}$$

$$a_{iR_K N_p} \leq \alpha_{iR_K N_p} \leq b_{iR_K N_p} \; \forall i, p = 1, \dots, P \quad \text{(Eq. 2.13)}$$

$$u_r, v_i, \alpha_{iR_K N_p} \geq 0 \; \forall i, R_K, p \quad \text{(Eq. 2.14)}$$

For each BHC, an aggregate efficiency score is derived and denoted by e_{agg}. Cook et al. (2013) argue that when a unit (DMU) consists of a set of subunits then it is reasonable to argue that from an accounting perspective, the "importance" of a given subunit relative to the full collection of such subunits can be expressed as the ratio of the weighted inputs consumed by that subunit to the total weighted input consumed by the full set. Specifically, the weight $W_{R_K j_0}$ for each subunit is defined based on the proportions of the aggregate inputs across the subunits (Cook et al., 2013). Therefore, we write

$$W_{R_K j_0} = \sum_{i \in I_K} v_i \alpha_{iR_k p^0} x_{ij_0} / \sum_{R_K \in L_{N_{p0}}} \left[\sum_{i \in I_K} v_i \alpha_{iR_k p^0} x_{ij_0}\right] \quad \text{(Eq. 2.15)}$$

For each group $\in L_{N_P}$, the proportions for each shared input add up to 1. Specifically, as argued in Cook et al. (2012, 2013), the variables $a_{iR_K N_p}$ and $b_{iR_K N_p}$ should be selected in such a way that the efficiency ratio corresponding to the group N_p and subunits R_k does not exceed unity for at least some values of u_r and v_i. In Copeland (2012), the author analyses BHCs' multi-year income structures and shows that the proportion of traditional income to total income is no more than 0.8 and that the proportion of the other income streams are generally ranging around 0.1. As such, the output for each subunit is calculated based on the actual income stream, and the values for the lower and upper limits $a_{iR_K N_p}$ (0.1) and $b_{iR_K N_p}$ (0.8) are determined based on the historical income structures from Copeland (2012).

The linear transformation is available in *Appendix 1.4* of Supplementary Materials and based on that, the optimal input splits $\alpha_{iR_K N_p}$ is obtained by observing that $\hat{\alpha}_{iR_K N_p} = \hat{\gamma}_{iR_K N_p} / \hat{\vartheta}_i$ (equations can be found in *Appendix 1.4*: Linear transformation). Once the split in the resources has been decided, we continue to obtain the subunit efficiencies by allocating resources according to the proportions $\alpha_{iR_K N_p}$.

It is noteworthy that only shared inputs are considered in our resource-allocation model since our objective is to optimize these shared resources into income subunits. In the case where "unique" or specialized resources are assigned to certain income-generating activities, dedicated inputs can be considered. Cook et al. (2000) and Cook and Hababou (2001) discuss shared and dedicated resources in a bank branch setting. However, in the current setting, due to the restrictions of our database, no such information can be extracted. Methodologically, any dedicated inputs can be combined with shared inputs as part of the input bundles and thus, will not affect the following steps in our model.

Step 2: Deriving the subunit efficiency scores

Three subunits appear in our model (i.e., one subunit for each income-generating stream). To obtain the efficiency of each subunit, a conventional DEA model is applied with a dedicated output and allocated inputs. For any DMU j_0 in a certain subunit R_K, efficiency is derived as follows.

$$\boldsymbol{e_{R_{K^0} j_0}} = \mathbf{max} \sum_{r \in R_{K^0}} (\boldsymbol{\mu_r y_{rj_0}} + \boldsymbol{\mu_k^0}) \quad \text{(Eq. 2.16)}$$

subject to

$$\sum_i \boldsymbol{\vartheta_i \tilde{x}_{ij_0}^{K^0}} = \mathbf{1} \quad \text{(Eq. 2.17)}$$

$$\sum_{r \in R_{K^0}} \boldsymbol{\mu_r y_{rj}} - \sum_{i \in I_K} \boldsymbol{\vartheta_i \tilde{x}_{ij_0}^{K^0}} + \boldsymbol{u_k^0} \leq \mathbf{0} \quad \boldsymbol{j} \in \boldsymbol{N_P} \quad \text{(Eq. 2.18)}$$

$$\boldsymbol{\mu_r}, \boldsymbol{\vartheta_i} \geq \boldsymbol{\varepsilon} \quad \text{(Eq. 2.19)}$$

Step 3: Deriving the aggregate efficiency scores (e_{agg})

Finally, with the derived resource splits $\alpha_{iR_K N_p}$, the weights $W_{R_K j_0}$ for each DMU's subunit efficiency scores $e_{R_{K^0} j_0}$, and the aggregate efficiency score e_{agg} of each DMU can be calculated by considering the weighted average of all the subunit scores $e_{R_{K^0} j_0}$and using the corresponding weights $W_{R_K j_0}$ as follows. The aggregate efficiency scores are derived by linking weights to the inputs–outputs bundle associated with each subunit, and as a result, simultaneously consider both internal structure issues and resource allocation requirements.

$$\boldsymbol{e_{agg}} = \sum_{R_K} \boldsymbol{W_{R_K j_0}} \, \boldsymbol{e_{R_{K^0} j_0}} \quad \text{(Eq. 2.20)}$$

Cook et al. (2013) show that the VRS setting in this model offers advantages in exploring the current resource management status (advising whether the returns to scale is increasing, constant, or decreasing) and in guiding managers in deciding how to reallocate resources across income-generating activities. The returns to scale implication, drawn from exploring the free of sign variable μ_k^0, is discussed in Section 6.

2.4.3 Bootstrapped truncated regression

After measuring the aggregate efficiency of BHCs by applying the resource-allocation model, a second stage analysis is conducted to examine the impacts of selected explanatory variables. Since the aggregate efficiency scores are obtained from an externally estimated DEA model, which was originally designed to address non-homogeneous and resource allocation issues, we adopt Simar and Wilson's (2007) bootstrapped truncated regression approach and consider the externally estimated aggregate scores as the dependent variable. We note that, as suggested in K. Du et al. (2018), frontier settings should consider the time effect in the context of panel data and thus, different frontier settings can be considered as comparisons. However, as aggregate efficiency scores are obtained from the external DEA model separately for each time point, our study only considers annual frontiers in the second stage analysis.

The following model is used for the second analysis with a bootstrap of 2000 replications, and this model includes the explanatory variables:

$$\hat{\boldsymbol{e}}_{\boldsymbol{j}}^{\boldsymbol{t}} = \boldsymbol{\beta}\, \boldsymbol{Z}_{\boldsymbol{j}}^{\boldsymbol{t}} + \boldsymbol{\gamma}\, \boldsymbol{D}_{\boldsymbol{j}}^{\boldsymbol{t}} + \boldsymbol{\varepsilon}_{\boldsymbol{j}}^{\boldsymbol{t}} \qquad \text{(Eq. 2.21)}$$

where $\hat{e}_j^t$ is the aggregate efficiency scores obtained from our resource-allocation model; Z_i^t refers to the explanatory variables of BHC j at time t, and D_j^t refers to the control variables, including year dummies. Following Simar and Wilson (2007), the model assumes $\varepsilon_j^t \sim N(0, \sigma_\varepsilon^2)$, which is independent of Z_i^t and D_j^t.

We acknowledge that "*any model is by necessity a simple abstraction of reality and thus, the maintained assumptions are rarely true in their entirety in practice. The key question is to what extent the assumptions deviate from reality and reasonable expectations based on prior research*" (Banker et al., 2019. p. 383). An important assumption to use the two-stage analysis (Simar & Wilson, 2007) is to meet the separability condition. The "separability" concerns have been well documented in Simar and Wilson (2011) and other studies. Daraio et al. (2018) argue that environmental factors would impact the shape of the frontier, the attainable set of values, and the distribution of inefficiencies inside. As such, "the second-stage analysis can only be meaningful if the separability condition holds." (Daraio et al., 2018; Simar & Wilson, 2011). To test the separability conditions, we follow the instructions in Daraio et al. (2018) and compare the means of conditional and unconditional efficiencies. The detailed steps and results are summarized in Appendix 1.5. The analyses (as shown in *Appendix 1.5* of Supplementary Materials) suggest no violation of the separability condition (Simar & Wilson, 2007), which thus allowed us to move forward to the second-stage analysis.

2.5 Results

In this section, the results of the conventional DEA model are presented first, followed by the findings from the Malmquist index analysis. Finally, we present the results of our resource-allocation model, together with the empirical findings from the bootstrapped truncated regressions in the second stage analysis. We conducted outlier diagnostics both prior-to-DEA and prior-to-second stage analysis. In our study, because BHCs show large variations in terms of size, income, and so on, the prior-to-DEA diagnostic was conducted to ensure BHCs do not have any unusual or extreme values from time to time.

2.5.1 Results from the conventional DEA model and the Malmquist index analysis

Table 2.3 summarizes the estimated efficiencies obtained from the output-oriented DEA model. In general, BHCs exhibit decreases in efficiency (i.e., inefficiency scores tended to increase each year) from 2010 to 2016. However, so far, limited insights can be drawn from the output-oriented conventional DEA model. More importantly, this model fails to address the existing non-homogeneity concerns among BHCs and the allocation of resources internally.

Table 2.3: Summary of efficiency scores based on the conventional DEA model

Year	2010	2011	2012	2013	2014	2015	2016
Average	1.84	1.87	1.92	2.00	2.01	2.04	2.01

Since we used panel data in this study, the Malmquist Index is useful in showing the changes over time. Table 2.4 shows the Malmquist index and its components *(EFFCH and TECHCH)* by peer group, including both year-by-year results and the six-year change from 2010 to 2016. First, we observed that the component *EFFCH* shows a value of only 0.844 (i.e., less than 1) in a six-year change, indicating that resources were not allocated equally efficient from 2010 to 2016. This resource optimization issue deserves attention. This concern applies to all BHCs regardless of peer group. Second, the component *TECHCH* is greater than 1 in all peers over time, suggesting that technological progress has occurred. Furthermore, the six-year change of *TECHCH* even reaches 1.135, which indicates a dramatic 13.5% technological improvement from 2010 to 2016. One could expect that technological progress like this would contribute to higher BHC performance. However, when checking the productivity changes over time, we found that in general, BHCs were continuously experiencing decreases in productivity year-by-year. The six-year (i.e., from 2010 to 2016) change in productivity is 0.946, which indicates an overall moving away from the best-practice frontier. Clearly, even though dramatic technological progress occurred from 2010 to 2016, it cannot offset the losses caused by the decreasing efficiency changes. As a result, BHCs kept experiencing productivity decreases. The results from the Malmquist index analysis motivated us to explore BHCs' internal structures and their income-generating activities and more importantly, investigate how resources can be allocated and reallocated efficiently. To this end, an input-oriented study was more appropriate to use because the goal is to show BHCs how to properly control and optimally allocate resources.

Table 2.4: Summary of the Malmquist index and its components

Year	Index	2010–11	2011–12	2012–13	2013–14	2014–15	2015–16	2010–16
Peer 1	*M*	0.962	0.98	0.981	0.981	0.976	1.019	0.910
N_1=34	*EFFCH*	0.893	1.031	0.942	1.007	1.014	0.970	0.852
	TECHCH	1.084	0.969	1.041	0.975	0.965	1.051	1.086
Peer 2	*M*	1.070	0.975	0.989	1.000	1.019	1.019	1.032
N_2=26	*EFFCH*	0.946	1.004	0.954	1.016	1.035	0.959	0.897
	TECHCH	1.131	0.970	1.037	0.985	0.985	1.063	1.157
Peer 3	*M*	0.962	1.022	0.912	1.007	1.007	0.998	0.898
N_3=21	*EFFCH*	0.862	1.055	0.872	1.016	1.025	0.941	0.765
	TECHCH	1.119	0.969	1.047	0.992	0.985	1.061	1.187
Peer Avg.	*M*	0.997	0.997	0.965	0.994	0.998	1.014	0.946
N=81	*EFFCH*	0.902	1.029	0.928	1.012	1.024	0.959	0.844
	TECHCH	1.108	0.969	1.041	0.983	0.976	1.057	1.135

Note: Index and components EFFCH and TECHCH are displayed by peer group, including both year-by-year results and six-year change

2.5.2 Results from the resource-allocation model and bootstrapped truncated regressions

We then assessed BHC aggregate efficiency using our input-oriented resource-allocation model for non-homogeneous BHCs with shared inputs. *The* aggregate efficiency scores are summarized in Table 2.5 and visually displayed in Fig. 2.3. The results show that BHCs in Peer 1 are more efficient than those in the other peer groups. One may notice that the aggregate efficiency scores are low on average. We show in *Appendix 1.6* the subunits' efficiency scores $e_{R_K o j_0}$ and weights for each subunit $W_{R_K j_0}$ using the year 2010 as an example. The aggregate efficiency scores obtained from the input-oriented resource-allocation model capture the overall performance across all three income-generating activities while allowing us to compare BHCs with their true peers. Based on the subunits' efficiencies, we can see that not all BHCs can be efficient in all three subunits. Some BHCs may do excellent work in traditional banking activities, while others perform better in new financial services (i.e., securitization or non-traditional activities). To improve aggregate efficiency, efforts should be made to identify how to optimally allocate resources among the income-generating activities. A demonstration of the average resource splits by peer group is displayed in Figure 2.4.

Table 2.5: Summary of aggregate efficiency scores from the resource-allocation model

Year	2010	2011	2012	2013	2014	2015	2016	Yearly Avg.
Peer 1	0.32	0.31	0.33	0.34	0.33	0.37	0.37	0.34
Peer 2	0.23	0.26	0.27	0.27	0.25	0.30	0.25	0.26
Peer 3	0.26	0.24	0.26	0.26	0.25	0.29	0.30	0.27
Peer Avg.	0.27	0.28	0.29	0.30	0.28	0.33	0.31	0.30

Figure 2.3: Aggregate efficiency scores by peer group

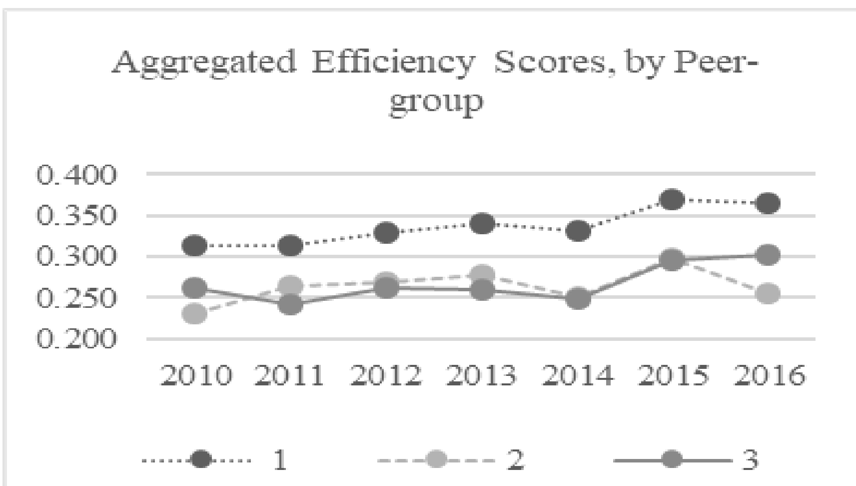
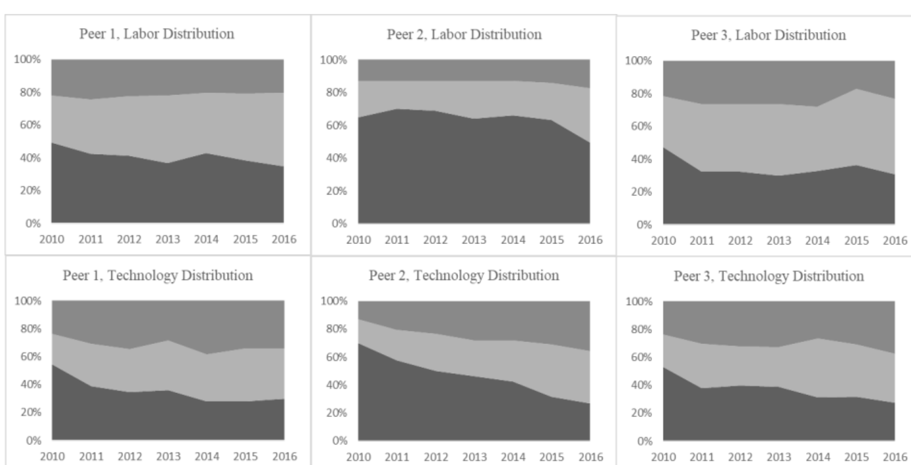


Figure 2.4: Labor and technology resource splits by peer group



We conducted the outlier diagnostics and Kernel estimated densities prior to the second stage analysis. Ten data points with aggregate efficiency scores equal to 1 were treated as potential outliers and removed. To compare the differences in distributions of aggregate efficiency scores with and without outliers, we followed the instructions in K. Du et al. (2018) and showed Kernel density estimates in Fig. 5 with two lines: (a) all data (*using dotted line*), and (b) data without outliers (*using solid line*). As presented in Figure 2.5, the distributions of scores remained similar with (*dotted line*) and without outliers (*solid line*), suggesting that the essential information about the distribution of aggregate efficiency scores was not affected by removing outliers (K. Du et al., 2018). Since the truncated regression automatically removes the data points with efficiency scores equal to 1, no further action was necessary at this stage.

To check for multicollinearity, the variance inflation factor (VIF) is presented in Table 2.6. All variables show small VIF values, indicating that minimal multicollinearity exists. The correlation matrix is also presented in Table 2.6. Hierarchical regressions are used, and the empirical results are presented in Table 2.7, along with the log-likelihood ratio, Akaike information criterion (AIC), and Bayesian information criterion (BIC). The efficiency scores we examined are the aggregate efficiency scores obtained from our resource-allocation model.

Figure 2.5: Outlier diagnostics using Kernel estimated densities of aggregate efficiency scores with and without outliers

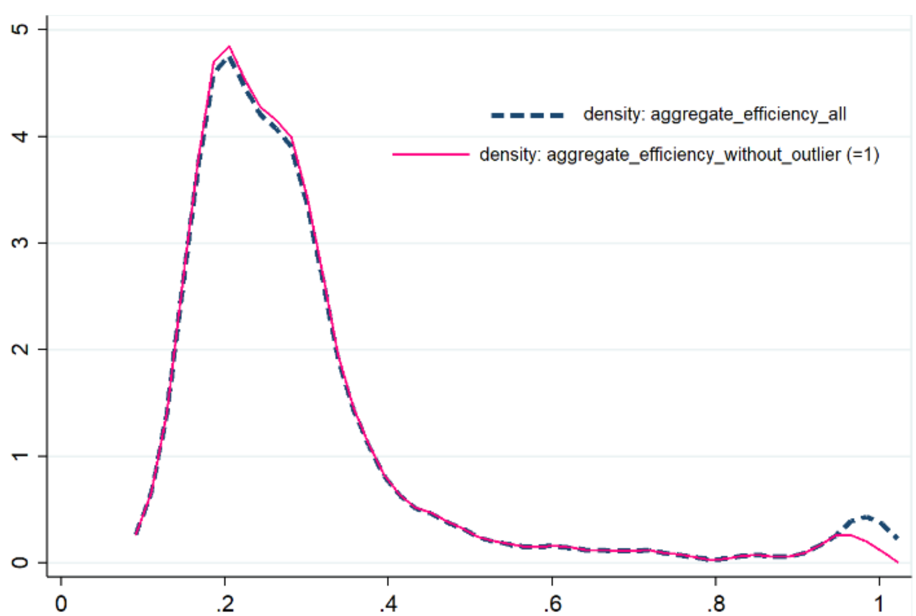


Table 2.6: Correlation matrix and variance inflation factors

Variable	Innovation Capability	Partnership	Peer group	Diversification	NPL	Capital Adequacy	VIF
Innovation Capability	1.00						1.10
Partnership	0.21*	1.00					1.12

Peer group	-0.18*	-0.01	1.00				1.15
Diversification	0.07	0.03	0.17*	1.00			1.05
NPL	-0.003	-0.25*	-0.14*	-0.02	1.00		1.09
Capital Adequacy	0.08*	-0.03	-0.22*	0.07	0.02	1.00	1.06
Mean VIF							1.10

Note: * at 10%.

First, the effects of BHC size (peer groups 2 and 3 as dummy variables) on aggregate efficiency are negative and significant. Particularly, the BHCs in Peer 1 is 0.052 higher than Peer 2 (b = -0.052) and 0.034 higher than Peer 3 (b = -0.034). The findings suggest that even though BHCs were compared against their true peers, size still matters. Second, the impact of BHC's innovation capability is significant and positive (b = 0.002), which suggests that BHCs with higher innovation capabilities are more efficient in resource optimization. This finding is consistent across all models. Third, the impact of BHC diversification on the aggregate scores is also found to be significant and positive (b = 0.056). In general, BHCs, which follow a diversification strategy, tend to be more efficient in managing resources than the specialized BHCs.

Finally, we assessed the impact of the partnership on the aggregate efficiency scores but found an insignificant coefficient. The finding seems to be in line with the BSRs literature in that a partnership does not necessarily bring direct benefits to the focal firms due to collaboration challenges (Sanders, 2007). However, to gain further insights regarding partnership, two interaction analyses were conducted, the results of which are shown in Table 2.7. We first considered the interaction term between peer group and partnership and include two interactions, namely *Peer (2) * partnership*, and *Peer (3) * partnership*. The coefficients of both interaction terms are negative and statistically significant, implying that having partnerships with technology firms has a moderating effect on the relationship between BHC size (peer group) and the corresponding aggregate efficiency scores. Marginal effects (shown in Table 2.8) were measured while keeping the other variables at their means, and the findings show that Peer 1 with a partnership has the highest predictive margin (0.318), outperforming the other peers. As shown in Figure 2.6, larger BHCs tend to perform better (i.e., with higher aggregate efficiency scores) if they have a partnership with technology firms, while smaller BHCs are more efficient when acting alone. We then assessed the interaction term between BHC diversification level and partnership, as shown in Model 4 of Table 2.7, but found no significant results.

To further validate our empirical results, we performed several robustness tests. We adopted the regular truncated models, Tobit models, and also the trans-log OLS. As shown in Table 2.9, consistent results can be found to support the robustness of our findings.

Table 2.7: Bootstrapped truncated regression results for aggregate efficiency scores

Models	(1)	(2)	(3)	(4)
Year				
2011	-0.013	-0.007	-0.011	-0.006
2012	0.011	0.013	0.009	0.013
2013	0.010	0.010	0.002	0.009
2014	-0.015	-0.012	-0.020	-0.013
2015	0.014	0.014	0.007	0.013
2016	0.017	0.014	0.007	0.013
Capital Adequacy	1.586***	1.272***	1.399***	1.263***
NPL	-2.268**	-2.413**	-2.547**	-2.413**
Innovation Capability		0.002***	0.002***	0.002***
Peer group				
Peer (2)		-0.052***	-0.001	-0.052***
Peer (3)		-0.034*	0.031	-0.033*
Partnership		-0.003	0.060**	0.028
Peer (2) * Partnership			-0.093***	
Peer (3) * Partnership			-0.119***	
Diversification		0.056**	0.057**	0.075*
Partnership * Diversification				-0.034
Constant	0.108**	0.0878*	0.048	0.072
N	557	557	557	557
sigma	0.163***	0.157***	0.155***	0.157***
Log Likelihood	305.721	321.873	328.165	322.104
AIC	-591.442	-613.747	-622.329	-612.208
BIC	-548.216	-548.908	-548.845	-543.047

Notes: Significance levels are used as follows: ***, 1%; **, 5%; and *,10%. The estimations are based on Simar and Wilson's (2007) algorithm 1 with the bootstrap of 2,000 replications.

Figure 2.6: Interaction effect of partnership and peer group

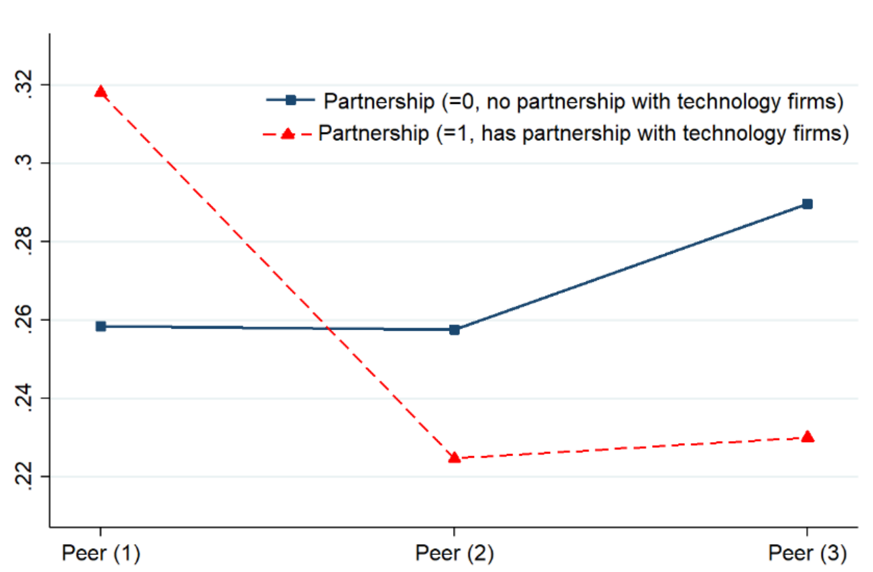


Table 2.8: Marginal effect of the interaction term, at means

Peer group * Partnership	Margin	Std. Err.	Z	P>|Z|	[90% Conf. Interval]	
1 0	0.258	0.018	14.500	0.000	0.229	0.288
1 1	0.318	0.017	19.530	0.000	0.291	0.345
2 0	0.258	0.020	13.030	0.000	0.225	0.291
2 1	0.224	0.019	12.080	0.000	0.194	0.255
3 0	0.290	0.021	13.720	0.000	0.255	0.324
3 1	0.230	0.021	10.870	0.000	0.195	0.265

Table 2.9: Robustness checks for aggregate efficiencies from the resource-allocation model

Models	Truncreg 1	Truncreg 2	Tobit 1	Tobit 2	OLS 1	OLS 2
Year						
2011	-0.009	-0.005	0.006	0.009	-0.006	0.001
2012	0.007	0.010	0.019	0.022	0.041	0.049
2013	0.002	0.007	0.017	0.023	-0.001	0.014
2014	-0.016	-0.011	0.003	0.009	-0.024	-0.009
2015	0.005	0.010	0.042	0.048	0.101	0.115
2016	0.006	0.010	0.027	0.032	0.056	0.068
Capital Adequacy	1.214***	1.101***	1.087***	0.998***	2.722***	2.463***
NPL	-2.007**	-1.947**	-0.427	-0.256	-3.398	-3.037
Innovation Capability	0.002***	0.002***	0.003***	0.003***	0.007***	0.008***
Peer group						
Peer (2)	-0.002	-0.043***	-0.011	-0.058***	-0.015	-0.123***
Peer (3)	0.025	-0.027*	0.012	-0.041**	0.069	-0.072
Partnership	0.050**	0.018	0.049**	-0.037	0.116*	-0.068
Peer (2) * Partnership	-0.076***		-0.089***		-0.202**	
Peer (3) * Partnership	-0.099***		-0.098***		-0.263***	
Diversification	0.045**	0.056**	0.030	0.014	0.097*	0.072
Partnership * Diversification		-0.0237		0.033		0.051
Constant	0.097**	0.122***	0.087*	0.134***	-1.834***	-1.728***
N	557	557	567	567	567	567
sigma	0.140***	0.139***	0.163***	0.164***	[R^2] 0.158	[R^2] 0.142
Log Likelihood	306.125	299.866	203.634	198.456	-292.2978	-297.7462
AIC	-578.250	-567.733	-373.267	-364.911	616.5956	625.4925
BIC	-504.766	-498.572	-299.481	-295.466	686.0413	690.5979

Notes: Significance levels are used as follows: ***, 1%; **, 5%; and *,10%.

2.6 Contributions, Implications and Discussion

Our study offers several theoretical contributions as well as managerial implications for practitioners, such as bank executives, investors, and policymakers. The limitations of this study and recommendations for future research are also discussed in this section.

2.6.1 Theoretical contributions

First of all, our study develops a new resource-allocation DEA model, which allows non-homogeneous BHCs to be benchmarked against their true peers and simultaneously optimize the allocation of those resources to income-generating activities. The non-homogeneity issue has been discussed in banking studies, such as Copelan (2012). However, previous studies using DEA techniques mainly focus on bank-level or bank-branch level efficiency without addressing the non-homogeneous concerns among banks. Particularly, previous studies have traditionally treated "income" as a single output and overlooked the inherent heterogeneity in the banking industry. This study leverages the relevant studies on non-homogeneity issues (Cook et al., 2012, 2013) and develops a new resource-allocation model, which: (a) identifies the non-homogeneity nature among BHCs based on their income structures, (b) evaluates the aggregate efficiency scores that can be used to benchmark with true peers of BHCs, and (c) allows resources (labor and technology) to be re-allocated optimally within BHCs. To this end, our study contributes to the DEA literature by demonstrating that income can play an intuitive role in differentiating BHCs and non-homogeneous BHCs can be benchmarked against their true peers while optimizing resources allocation simultaneously. We acknowledge that different methods to address the non-homogeneity issues also exist, for example, J. Du et al. (2015) focused on the non-homogeneity issues in network DEA models. Zhu et al. (2018) address the non-homogeneity issue using a cross-like efficiency model, which generates and utilizes the unique rankings of DMUs. Determine how to address the non-homogeneity issue may depend on the different sources of non-homogeneity in the data set. Here, even though these methods are not the best options for this study considering the nature of non-homogeneity in BHCs, we expect future studies may draw greater attention to the non-homogeneity issues. Moreover, as we observe, the shift from traditional banking to digital banking is still ongoing, and a growing number of digital-only banks have emerged. Therefore, it is likely that future DEA studies could extend the analysis by applying it to a broader context. We also expect that future studies could contribute by applying different experimental methods for validation, such as conducting Monte Carlo experiments to examine the performance of DEA methods (Cook & Zhu, 2014).

By examining the impacts of explanatory variables on BHCs' aggregate efficiency scores, this study also contributes to the relevant literature by offering empirical evidence. First, our findings illustrate that size does matter, especially when considering BHC aggregate efficiency. This finding offers evidence against the existing contradictory results on "size" (Paradi et al., 2011; Drake & Howcroft, 2002) by showing that larger BHCs tend to perform better (beneficial more from their digital investment) than smaller BHCs. Large BHCs could have well-established operating systems that offer advantages in resource planning, controlling, and distributing, consequently leading to higher aggregate efficiency scores. While this study uses peer groups as a proxy for size, future studies could examine this by using other measures.

Second, this study contributes to the literature on technology management and shows that BHCs with stronger innovation capability are more efficient than the others. The capability-performance relationship is intuitively accepted and empirically examined in other contexts but not in the context of digitalization in the banking industry. Particularly, previous studies have only discussed the innovation capability conceptually without empirical measurement and examinations. By leveraging the RBV, we measure a BHC's innovation capability in terms of intangible elements such as patents, intelligence rights, and so on. (Lawson & Samson, 2002). Our findings empirically reveal that stronger innovation capabilities can drive higher efficiencies in allocating valuable resources, thus encouraging greater emphasis on developing, managing, and transferring the unique and hard-to-imitate knowledge and intelligence into valuable competitive advantages in the digital age. While we use available secondary data to measure innovation capability, future studies could investigate whether this relationship holds by using other measures.

Third, our study contributes to the banking diversification literature by empirically showing that more income-diversified BHCs do better jobs in resource utilization compared with more income-specialized BHCs. Previous studies have not sufficiently examined whether diversification or specialization strategy makes banks more efficient (Curi et al., 2015). Additionally, even though existing studies have discussed the potential ways to measure diversification, insufficient empirical examinations have been provided. In this study, we measure and offer empirical evidence about the effects of diversification on BHCs' aggregate efficiency.

Finally, our study contributes to the study of BSRs by empirically showing the impacts of collaborating with FinTech firms in the banking context. Previous BSRs literature suggests that the complexity of collaboration and the required effort may prevent focal firms from benefiting directly from partnerships (Sanders, 2007). Nevertheless, our results show that collaborating with FinTech firms has a moderating role between BHC size and aggregate efficiency performance.

Particularly, larger BHCs (peer group 1) perform better in managing and utilizing their (human and digital) resources by collaborating with technology firms, while smaller BHCs are better off to play alone. Particularly, since FinTech collaboration has only been discussed in previous studies without any empirical examinations, this study provides, to our best knowledge, the first empirical evidence of how collaborating with FinTech firms benefits BHCs. The examination of the moderating effect may help to further push the boundary conditions and better understand the bank-FinTech relationship. We acknowledge that this study only considered the existence of such a relationship as a binary state – presence or absence. However, the impact of collaborating with FinTech firms may also be affected by other FinTech firm-related characteristics. For example, the form of collaboration structure, the extent or the length of collaboration, the types of work provided by FinTech firms, the nature of FinTech firms as an established one or start-up, and so on. We suggest future studies to further explore how FinTech collaboration and its relevant characteristics would contribute to BHC performance.

2.6.2 Managerial implications

Rather than evaluating how much cost can be reduced by digital technologies in a particular BHC, this study evaluates the return of investment in digital technologies and especially evaluates the relative performance of BHCs by benchmarking their true peers. Back to our initial question, has technological investment been worth it? Given the results from the Malmquist index analysis and the resource-allocation model, the answer is unfortunately no. However, our research findings imply that the reason is not the technology itself but rather the inefficient resource management over time. Such a finding is extremely important for bank executives and investors, especially when the entire banking industry is pursuing more cutting-edge technologies but ignoring the necessity of upgrading daily operations, especially with regard to optimizing resources, both human and digital resources. For BHCs, it is important to improve performance operationally by adopting efficient practices or switching to better systems, rather than relying solely on technology.

Furthermore, should BHCs rely upon internal or external to drive performance? Internally, we show that BHCs can perform better by improving their innovation capabilities. Externally, our findings imply that collaborating with FinTech could be a good option for larger BHCs when pursuing higher aggregate efficiency scores. However, this is not a must-have for smaller BHCs. For larger BHCs, building a partnership offers them opportunities to leverage emerging technologies. However, for smaller BHCs, working with FinTech may require BHCs to develop mutual strategies, share resources and information, appoint dedicated teams, adapt culture differences, develop a more cooperative process, and so on, thereby leading to greater challenges and difficulties in collaborating. This study, therefore, sheds light on the ongoing debate regarding bank–FinTech collaboration.

Finally, combined with the VRS setting used in our resource allocation model, we offer the following practical insights on allocating and reallocating resources. The splits of resources, shown in Figure 2.4, illustrate that the allocation of labor and technology has changed over time. Human resources have been largely used in traditional banking activities but maintained at a low level in non-traditional banking activities. More technology resources have been shifted from traditional banking services to new financial services and securitization. When exploring the free of signs variables μ_k^0 (presented in *Appendix 1.7* of Supplementary Materials) obtained from the resource-allocation model, we observe that more specialized BHCs (i.e., those involved only in traditional and/or securitization activities) tend to enjoy increasing returns to scale over time, hence suggesting these BHCs are allocating resources to their most promising banking segments. By contrast, the more diversified BHCs, especially those in Peer 1, tend to experience either occasional or continuous decreasing returns to scale. For them, the current business is becoming mature and thus, when they continue to expand, it is very challenging to increase output by replicating existing operational practices. Such information is important for BHCs and policymakers, as they should pay close attention to resource management and reasonable expansions.

2.7 Conclusions

In this study, we develop a new model to evaluate banks' digital investment and explain why they wasted money on digital. Our model simultaneously considers the non-homogeneous nature among BHCs as well as the necessity of allocating shared resources. This study makes contributions to the DEA literature by identifying and addressing non-homogeneity concerns via the view of "incomes." Furthermore, our findings suggest that an efficient resource management strategy is imperative; otherwise, BHCs cannot bring in benefits from technological advancement. Our paper also contributes to the banking performance literature by examining the relevant explanatory variables. The empirical results supplement the existing literature by showing how BHC size and diversification make a difference in BHC performance. We contribute to the technology management literature by employing intangible resources as a measure of BHC innovation capability and by examining its impact on driving higher BHC performance. Most importantly, our study complements the broader BSRs literature in the banking context by providing empirical support for the association between the bank–FinTech partnership and BHC performance. In particular, a moderation effect exists whereby larger BHCs are more likely to gain an advantage from having a partnership with technology firms, but smaller BHCs are better off not collaborating with FinTech firms. Finally, we hope this study delivers a straightforward message to both BHCs and policymakers that adopting technologies without a thorough review of existing operations would end up being inefficient and a waste of resources. Investment and expansion are decisions that should always be made thoughtfully.

Chapter 3

Digitizing Retail Banking Services: An Empirical Examination of Drivers and Outcomes of Digitization Capability

Abstract

This study investigates the digitization of retail banking services in retail banks and credit unions. We propose a theoretical model to examine the drivers and outcomes of elevating digitization capability. Especially, in this model, marketing-level strategic decisions (i.e., digital-savvy customer focus) and operational efforts (i.e., front-office back-office process alignment) are considered key drivers of digitization capability, and the improvement in business performance (e.g., increase in customer base, market share growth) and objective financial performance (i.e., change of ROA and ROE) are considered outcomes of elevating digitization capability. To empirically test the model, we collect both primary data via a web-based survey and secondary data via available annual reports. Results show that elevating digitization capability helps retail banks and credit unions improve their performance. We also find that, focusing on digital-savvy customers and aligning front-office back-office process are acting as important drivers for retail banks and credit unions to enhance their digitization capability. Particularly, our study demonstrates that digitization capability acts as a mediator to explain how strategic and operational efforts are transformed into improved performance.

Keywords: Digitization capability; Digitization of retail banking services; Retail banking units

3.1 Introduction

Through the implementation of emerging digital technologies (e.g., AI, mobile technology), an increasing number of retail banking services are now offered digitally (Barrett et al., 2015; Basole & Patel, 2018; Gomber et al., 2017; Wewege & Thomsett, 2019). *Digital retail banking services* refers to services that utilize emerging digital technologies (e.g., mobile technology, AI, big data), can be accessed and delivered through multiple digital channels (e.g., website, app, social media) using various digital devices (e.g., PC, mobile, tablet, wearable device) and are designed to be entirely automated — delivered to customers without physical interface with human service providers. Although retail banks and credit unions (retail banking units, hereafter referred to as "RBUs"[1]) have a longstanding commitment to invest in and utilize digital technologies to digitize service offerings (CBA, 2019); however, the failure rate remains high. Globally, more than 70% of digital initiatives have not yet reached the goal (McKinsey, 2016) and the digitization failure rates are high, ranging from 60% to 85% (Siemens IoT Services, 2019).

One possible explanation for such a high failure rate is the lack of digitization capability. Even though relevant industry reports (e.g., Accenture, 2019; Capgemini, 2019; Deloitte, 2020) and academic studies (e.g., (Chen et al., 2019; Holmlund et al., 2017; D. Liu et al., 2011) have highlighted the importance of digitization capability to gain competitiveness and success in the digital age, some banks still lack interest in developing and continually elevating their digitization capability (Holmlund et al., 2017; Deloitte, 2020). The existing literature has provided limited insights into digitization capability. Scholarly understanding of digitization capability is primarily based on case studies on the digitization story of a particular bank and thus remains largely conceptual and inconsistent (e.g., D. Liu et al., 2011; Sia et al., 2016). No study to date has empirically measured the digitization capability of RBUs or explored its drivers and outcomes. It is yet unclear what would help RBUs to build their digitization capability and how digitization capability would lead to better performance.

We propose that there is insufficient exploration of the key drivers of the development of digitization capability. From the marketing strategy perspective, the digitization journey should start with a thorough understanding of the customers. Most retail banking users today are digitally savvy. Nearly 90% of Canadians do most of their banking via digital channels and over 30% are digital exclusively (OliverWyman, 2017). It is estimated that by the end of 2025 the number of

[1] Formally defined, retail banking units (RBUs) are "the strategic business unit, which may be an entire bank, a holding company, a division or group, or department, depending on how the retail side is organized" (Roth, Schroeder, Huang, & Kristal, 2007, p.16). This study uses RBUs to represent retail banks and credit unions.

digital retail banking services users in the U.S. will reach 217 million (~ 80% of the population) (Insider, 2022), and over 40 million will be digital-only users (Insider, 2021). Globally, the number of digital banking users is expected to exceed 3.6 billion by 2024 (Juniper Research, 2020). Not only younger customers are digital savvy. A survey conducted by Javelin Strategy & Research (2019) shows that 65% of Baby Boomers (born from 1946–1964) now rely on digital retail banking services just like Millennials (also called Generation Y, born from 1981–1996) do. The COVID-19 epidemic has also pushed more traditional, face-to-face banking users into digital users and further transformed their ways of banking. Considering these, should RBUs focus on digital-savvy customers, and so, how would this benefit their digitization of retail banking services?

Other than the strategic decisions that guide RBUs to focus on the right customers, we propose that the internal efforts of RBUs may also critically impact their digitization capability. Though an increasing number of retail banking services are now offered digitally (e.g., online banking, bill paying, bank transfers), customers are still experiencing uncertainties and interruptions. The interactions via self-served digital retail banking services frequently fail for customers; for instance, customers reported that the services are too complicated, took too long to complete, or did not provide all information they needed (BT and Avaya, 2016). From the operational perspective, these problems could be caused by the misalignment between the customer-serving front-end and the supporting back-end within RBUs. For service providers, the alignment within the entire organization, across the front and back offices, is required to deliver a seamless customer experience (McKinsey, 2019; KPMG, 2018). Yet, it remains unclear what RBUs need to do internally to enhance their digitization capability and gain better performance from offering digital retail banking services to customers.

This paper focuses on the digitization of retail banking services in retail banks and credit unions (RBUs). It aims to provide theoretical and empirical evidence as to why digitization efforts have failed to improve performance by exploring and answering the following three research questions: (i) *What is the impact of the digitization capability on business performance improvement?* (ii) *What is the impact of focusing on digital-savvy customers on the digitization of retail banking services?* (iii) *What is the impact of aligning the front-office back-office process on the digitization of retail banking services?*

We first define a new construct, the *capability to digitize retail banking services*, to empirically evaluate the efforts of RBUs to continuously integrate emerging digital technologies into the digitization of retail banking services. Notably, since digital technologies can be purchased from external sources (Sia et al., 2016), any digital technology alone delivers little or limited value to firms (Vial, 2019). We propose that, rather than possessing digital technologies, it is the ability of RBUs to orchestrate (combine, deploy, integrate) these digital resources to build relevant capability that enables them to gain competitive advantages and in turn achieve superior performance (Sirmon et al., 2007, 2011). We utilize the resource-based view and the resource orchestration theory to propose and empirically test the impact of the capability to digitize retail banking services on performance improvement. This study also proposes and tests the drivers of digitization capability. We consider *digital-savvy customer focus* as the *strategic driver* and *front-office back-office process alignment* as the *operational driver* for developing and enhancing digitization capability. We leverage the literature on internal process integration (Braunscheidel & Suresh, 2009; Flynn et al., 2010; Narayanan et al., 2011; Schoenherr & Swink, 2012; C. Y. Wong et al., 2011), front-office back-office operations (Froehle & Roth, 2004; Menor et al., 2001; Zomerdijk & De Vries, 2007), market segmentation (Kaynak & Harcar, 2005), and customer centricity (Fader, 2012).

To examine our model, we collect primary data from 32 retail banks and 92 credit unions in Canada via a web-based survey and also collect secondary data via their annual reports from 2020 to 2021. Our findings show that digitization capability is positively associated with performance improvement. For RBUs to improve their performance in this digital age, they have to develop and enhance their ability to integrate emerging digital technologies to digitize their retail banking services. Our findings also show that focusing on digital-savvy customers and aligning front-office back-office processes act as key drivers that contribute to the digitization capability of RBUs.

This research offers two theoretical contributions. First, we define a new construct, *capability to digitize retail banking services*, and we develop a new measurement scale for it. These could potentially help RBUs to succeed in the digitization of retail banking services. Second, this study proposes a new theoretical model and tests the drivers and outcomes of digitization capability. In the context of digitization of retail banking services, the decision to focus on digital-savvy customers and the operational efforts of aligning internal process would help enhance digitization capability, and further assist RBUs in improving their performance. Additionally, this study provides several practical insights into the digitization of retail banking services for RBUs. Specifically, it highlights the importance of developing and improving the ability of RBUs to integrate emerging digital technologies to digitize their existing face-to-face retail banking services into services to be offered digitally. To do this, RBUs should stay focused on digital-savvy customers and continuously synchronize their front-office back-office process.

3.2 Literature Review

3.2.1 Digitization of retail banking services and digitization capability

Since technologies act as the fundamental means for innovations of new service offerings (Barrett et al., 2015; Geum et al., 2017) and can potentially improve firm performance (Biemans et al., 2016), many studies on the digitization of retail banking services focus on the implementation and applications of one particular digital technology (Legner et al., 2017; Reis et al., 2018). For instance, early studies offer some empirical insights into the *early wave* digital technologies such as the internet and virtual agents (Basole & Patel, 2018). Previous studies argued that the internet served as a *complementary* delivery channel to physical banking channels (e.g., ATMs, in-branch visits) and improved banks' profitability over time (DeYoung et al., 2007; Hernando & Nieto, 2007). The virtual agent is used to improve interaction style, content, and customer usage (Köhler et al., 2011). However, when turning to the more advanced and emerging digital technologies (e.g., AI, big data), most studies are based on case studies of particular success stories (e.g., Lehrer et al., 2018) and provide limited insights into the use of emerging digital technologies (Breidbach et al., 2020; Gozman et al., 2018). For instance, one case study by Lehrer et al. (2018) explores the potential of utilizing big data analytics technology to enable highly customized digital retail banking services embedded with customers' profiles and preferences; however, no empirical examination has been conducted to investigate the impacts of adopting emerging digital technologies like big data. As Breidbach, Keating, and Lim (2020) argue, "research explicitly exploring the role and impact of new financial technologies on service systems is lacking" (p. 81). The retail banking industry is still lagging behind the digital technology trends and the digitization progress of other industries such as media (Gandhi et al., 2016; Harvey, 2016). Studies that explore why digitization efforts have failed and ways to continuously implement emerging digital technologies remain limited.

When turning to the ability that is required to digitize retail banking services, several studies have recognized the importance of developing digitization capability (e.g., Chen et al., 2019; Holmlund et al., 2017; D. Liu et al., 2011; Maiya, 2017; Sia et al., 2016); however, these studies present different views of digitization capability. For example, Maiya (2017) argues that becoming truly digital requires banks to strategically change from the inside and rethink the required capability in terms of using digital technologies. D. Liu et al. (2011) investigate the success story of a bank that participated in an e-banking project and emphasize the fit of resources and capabilities in meeting the demands of digital transformation. Particularly, they believe that more than one capability is required, including *IT integration* (i.e., the ability to leverage information technologies), *reconfiguration agility* (i.e., the ability to effectively reorganize existing resources), *collaboration* (i.e., the ability to connect to external customers and suppliers), and *customization* (i.e., the ability to innovate differentiated services/products). Sia et al. (2016) explore the digitization case of the DBS Bank (Singapore's leading consumer bank) and argue that banks must gradually build the capability to design new digitally enabled customer experiences and generate digital innovations. Sia et al. (2016) argue that since the technology itself can be purchased from external suppliers, it is critical for banks to build strong in-house competencies so that they can integrate technologies by themselves. Still, some studies argue that banks have not yet developed related capability to move forward (Holmlund et al., 2017).

Despite the important insights from previous studies, we identify the following gaps in the literature. First, empirical insights are largely limited to the individual application of early-wave digital technologies (e.g., the internet). Studies that explicitly explore the impacts of using more advanced and emerging digital technologies (e.g., AI, big data) remain lacking (Breidbach et al., 2020; Gozman et al., 2018). It is yet unclear whether previous insights can be generalized to other emerging digital technologies and how RBUs can continuously leverage and integrate such digital technologies into the digitization of their retail banking services. Second, although prior studies have highlighted the need for building digitization capability, our understanding of digitization capability is largely conceptual and varies across case studies. The insights have been drawn mainly from case studies of digitization in one particular bank (e.g., DBS Bank, Sia et al., 2016; CBC Bank, D. Liu et al., 2011), and thus, lack broad and deep empirical examination. Furthermore, the literature has not yet provided a clear definition of *digitization capability* nor has it *empirically examined* its impact on business performance.

Hence, in the context of digitization of retail banking services, since compelling and convincing operationalization and examination of digitization capability is lacking, this study helps to bridge this gap by empirically measuring and examining the impacts of digitization capability of RBUs. Drawing upon extant literature, we define *digitization capability* as the ability of an RBU to integrate and leverage emerging digital technologies to digitize retail banking services. We examine the outcomes of developing digitization capability and link it to performance improvement that RBUs can obtain. Additionally, we explore the key drivers that contribute to the development of digitization capability of RBUs.

3.2.2 Digital-savvy customer focus as a key driver for digitization capability

Customers are a focal point for banks aiming to be truly digital (Maiya, 2017). Since customers decide "where, when and how value is created," (Komulainen & Saraniemi, 2019. p. 1086), many studies on the digitization of retail banking services have discussed the role and impacts of *customers*.

Prior studies have investigated the determinants and outcomes of customers' adoption and continued usage of digital retail banking services (e.g., DeYoung et al., 2007; Oertzen & Odekerken-Schröder, 2019; M. Xue et al., 2011). The examined outcomes include customer-level performance (e.g., customer satisfaction and loyalty) (M. Xue et al., 2011) as well as firm-level performance (e.g., profitability growth) (DeYoung et al., 2007; Mbama et al., 2018). Important factors that affect customers' adoption of digital retail banking services include the various attributes of digital retail banking services, such as perceived usability (Oertzen & Odekerken-Schröder (2019), service customization (Mbama et al., 2018), customer interactions (Köhler et al., 2011; Larsson & Viitaoja, 2017), and customer experience (Shin et al., 2019).

Particularly, many studies have explored different ways to segment retail banking customers (e.g., Chawla & Joshi, 2017; Laukkanen et al., 2007; Laukkanen & Pasanen, 2008; Rober Rugimbana & Philip Iversen, 1994). Early studies tend to differentiate customers based on demographics (i.e., age, gender, education and occupation). For instance, Rugimbana and Iversen (1994) identify age as a segmenting variable to differentiate ATM users from non-users. Al-Ashban and Burney (2001) and Karjaluoto et al. (2002) consider age, education, and income level as key factors to segment online banking users and non-users. Despite the insights provided previously, these segmentations may be no longer applicable today. For example, Laukkanen and Pasanen (2008) find that education, income and occupation no longer act as differentiators for online or mobile banking adopters. More recent studies segment customers beyond the limits of demographics. For example, Rajaobelina et al. (2013) cluster online banking users based on relationship-related variables such as trust, satisfaction, and commitment. Chawla and Joshi (2017) segment mobile banking customers based on their perceptions of and intentions for using mobile banking.

Previous studies have also shown that customer behaviors of digital retail banking services users are also different than the traditional/non-digital customers. For example, M. Xue et al. (2011) find that customers who adopted online banking increased their consumption of services via the online channel, show greater interest in product acquisition from the primary bank, and establish a deeper and longer relationship with the bank. In another study conducted by Windasari et al. (2022), the authors explore the views of the digital-only banking experience of Gen Y (born from 1981–1996) and Gen Z (born from 1996–2012) and found that Gen Y and Z digital-only customers show greater affective commitment to banks with better digital service experience and are more willing to adopt digital services based on positive word-of-mouth (Windasari et al., 2022).

Recent studies have noticed that being customer-centric is important in the digitization of retail banking services (Komulainen & Saraniemi, 2019). Establishing customer-centric thinking can help banks identify the key role that customers play in creating value in the digitization of service offerings (Komulainen & Saraniemi, 2019). Thus, it is crucial for RBUs to identify their most valuable customers and what they need. However, at the same time, studies have also been aware of the challenges that customers bring to the digitization journey. For instance, Holmlund et al. (2017) argue that the *changes* in customers, such as lifestyle changes, increasing preference for digital interactions, and an increasing tendency to switch banks, are major challenges for retail banks, making it difficult for RBUs to stay focused in their digitization journey.

Despite the insights provided by the customer-related literature, prior studies have not explicitly explained, in the context of digitization of retail banking services, how to segment customers and which customers are ideal for RBUs, and thus which segment they should focus on. Given increasing digital demands and the potential returns from digital-savvy customers, it would be beneficial for RBUs to identify their most valuable customers based on customer preferences and behaviors and to strategically focus on digital-savvy customers. In this study, we consider such a marketing strategy as a key driver to motivate RBUs to develop their digitization capability and empirically investigate the impacts.

3.2.3 Front-office back-office process alignment as a key driver for digitization capability

Previous studies have discussed the importance and potential benefits of streamlining the process in the digitization of retail banking services (Banerjee, 2014; Sia et al., 2016; Yanagawa, 2018). For example, in a case study of one retail bank, Banerjee (2014) argues that the "misalignment" between the services and the channel (e.g., physical and virtual) may prevent customers from gaining a seamless experience and thus negatively impact the bank performance. For instance, misalignment occurs when a customer expects to receive face-to-face, professional investment advice but only receives general advice online. Banerjee (2014) argues that it is the integration and streamline of the front-office back-office processes and systems for service delivery that ensures both content and process consistency within and across channels. In a similar vein, Yanagawa (2018) emphasizes the importance of establishing frictionless processes that enable banks to seamlessly interact with customers and optimize their costs. To that end, Sia et al. (2016)

conduct a case study of the DBS Bank and argue that aligning processes (e.g., enabling cross-functional team collaboration) is critical in the digitization of services offerings and could dramatically save costs.

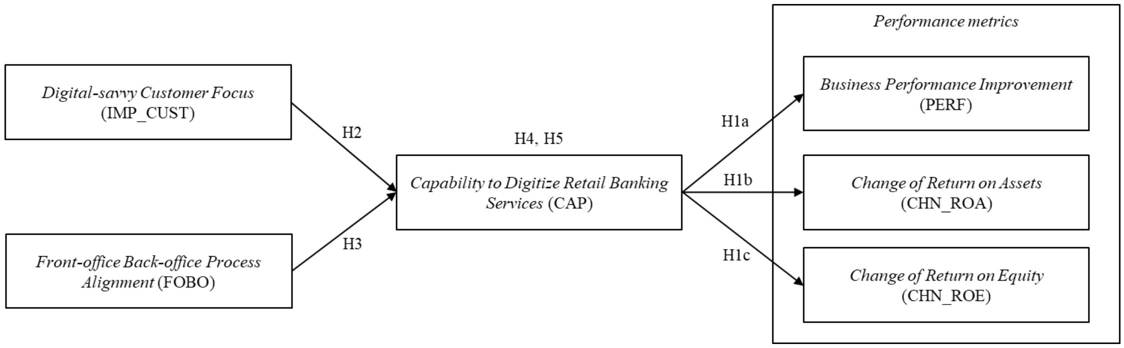
Prior studies have also emphasized the need to enhance customers' digital experiences and improve interactivity (Köhler et al., 2011; Komulainen & Saraniemi, 2019; Larsson & Viitaoja, 2017; Shin et al., 2019; Sousa et al., 2015). These studies have highlighted the importance of interactivity, which includes but is not limited to accessibility, efficient customer support, and timely communication (Larsson & Viitaoja, 2017; Shin et al., 2019). For instance, Köhler et al. (2011) explain how the interactivity between intelligent virtual agents and customers profoundly influences customers' attitudes and behaviors. Based on customer interviews, Komulainen and Saraniemi (2019) argue that better bank–customer interactions may improve the value for customers. Shin et al. (2019) provide empirical evidence that digital banking customers experience a lower level of bank–customer engagement, which in turn negatively affects customer satisfaction. Sousa et al. (2015) survey customers from one retail bank in the European Union and assert that matching the design of banking services with the best physical or digital channel would increase customers' usage of banking services (e.g., deposit and withdrawal transactions). By interviewing senior bank managers about their views on and experiences with digital banking, Mbama et al. (2018) assert that enhancing employee-customer interactions could improve the design of digital retail banking services, and also the financial performance.

The literature has generally overlooked the limitations of internal process alignment. Existing studies have only discussed the potential benefits of front-office back-office integration in the digitization of retail banking services, for instance, ensuring consistency (Banerjee, 2014), decreasing costs (Sia et al., 2016), and providing a seamless customer experience (Yanagawa, 2018). However, studies have not empirically examined the role and impact of the front-office back-office processes alignment on the digitization of retail banking services. Hence, in this current study, instead of building upon customers' views as has been done, we collect views from executives of RBUs to explore the operational efforts of RBUs. We consider aligning front-office back-office process as a critical factor that could motivate RBUs to build their digitization capability and consequently improve their performance.

3.3 Hypotheses Development

Figure 3.1 depicts the conceptual model for the hypotheses to be analyzed. Section 3 discusses the development of the hypotheses.

Figure 3.1: Conceptual Model



3.3.1 Capability to digitize retail banking services and business performance improvement

Capability to digitize retail banking services (CAP) refers to the ability of RBUs to continuously integrate and leverage emerging digital technologies to digitize existing retail banking services into those that are executable digitally by customers without human interactions. A broad set of digital technologies, including artificial intelligence, application development, big data, blockchain, cloud, Internet of Things, peer-to-peer, and robotics (Eling & Lehmann, 2018; Gomber et al., 2017), are resources available for deployment and integration. The resource-based view (RBV) of the firm has been widely used in service operations management studies to understand the effects of service firms' ability to integrate resources in the design and delivery of services (Menor & Roth, 2008). In the context of the digitization of retail banking services, since these digital technologies are resources that can be purchased from external sources (Sia et al., 2016), they are not rent-yielding per se, as rent-yielding resources are those that are valuable, rare, non-substitutable, and inimitable (Barney, 1991). Therefore, possessing such digital technologies is not enough to build and maintain competitive advantages. Digital technologies must be orchestrated (e.g., combined, structured, deployed, and integrated) to develop capabilities. It is such difficult-to-imitate capabilities that allow banks to outperform their peers and achieve superior performance (Sirmon et al., 2007, 2011). Particularly, since digital technologies rapidly advance, elevating such capabilities requires continuous efforts to integrate and leverage emerging digital technologies to digitize retail banking services to adapt to the changing environment (Kane, 2017). Therefore, drawing upon the RBV and the resource orchestration theory (Sirmon et al., 2007, 2011), it is critical for RBUs to continuously elevate their capability to digitize retail banking services to gain improvement in their business performance.

Prior studies in different contexts, such as retail management and supply chains, have examined the impact of a firm's ability to use technologies in operations on firm performance (Devaraj et al., 2007; Oh et al., 2012). Oh et al. (2012) define the IT-enabled retail channel integration capability of retail firms as the "ability to use IT in integrating their cross-functional channel resources and operations in their service delivery system" (p. 370) and assert that a stronger capability positively impacts firm performance (e.g., market share gains, net profits, and ROA). Devaraj et al. (2007) investigate eBusiness capability, which refers to the "ability of a firm to use Internet technologies to share information, process transactions, coordinate activities, and facilitate collaboration with suppliers and customers" (p. 1201). According to this study, although the firm does not derive direct benefits, a stronger eBusiness capability indirectly improves operational performance through the integration with customers and suppliers.

In the context of the digitization of retail banking services, we define the *business performance improvement* (PERF) of RBUs as the increased benefits (e.g., increase in profitability) realized from offering digital retail banking services to customers in comparison to their competitors. Offering new services benefits service providers in various ways, such as by increasing profitability, attracting new customers, and opening new markets (Menor et al., 2002). Several case studies on digitization also suggest that building relevant digitization capabilities helps to achieve superior performance (D. Liu et al., 2011; Sia et al., 2016). As such, we posit that RBUs can improve performance if they enhance their capability to digitize retail banking services. As RBUs continuously integrate emerging digital technologies to transform existing face-to-face retail banking services to be offered digitally, RBUs will be enabled to offer new digital services that can meet the increasing digital demands from customers, target new markets, locate new sources of revenue, attract customers away from competitors, and consequently, enhance their customer base, market share, and competitive position. Additionally, the increasing number of digital retail banking services can also complement traditional face-to-face banking services, allowing RBUs to interact with customers more efficiently with fewer employee inputs and thus deliver retail banking services with lower costs and higher profits. Conversely, if RBUs cannot continually elevate their capability to digitize retail banking services, they are unlikely to fully utilize the emerging digital technologies that they have invested in. As a result, they may fail to apply the technologies to banking services and instead offer similar or even unwanted digital retail banking services that negatively affect their performance. Therefore, we hypothesize that:

Hypothesis 1a. The capability to digitize retail banking services is positively associated with the change in business performance.

Additionally, as RBUs enhance their ability to digitize existing face-to-face retail banking services into services to be offered digitally without human interactions, the subsequent reduction of employees can dramatically reduce their costs and increase profits. Therefore, we also leverage two accounting-based financial measures to directly evaluate the impact of the capability to digitize retail banking services. Return on Assets (ROA) and Return on Equity (ROE) are widely-used profitability metrics that reflect how well a firm performs based on its total assets. These two measures are used in accounting-based, objective financial performance assessment in service operations studies (Menor & Roth, 2008; Narayanan et al., 2021; Yang et al., 2018). We, present our second hypotheses 1b and 1c.

Hypothesis 1b. The capability to digitize retail banking services is positively associated with the change in ROA.

Hypothesis 1c. The capability to digitize retail banking services is positively associated with the change in ROE.

3.3.2 Digital-savvy customer focus and capability to digitize retail banking services

Digital-savvy customer focus (IMP_CUST) refers to the tactics of RBUs to segment customers based on customer behaviors towards digital retail banking services and positioning the online embracers and digital adventurers, described below, as their most critical customers. Customers are classified into three segments: (i) *traditionalists* — customers who do most of their banking in person in branches and through ATMs; (ii) *online embracers* — customers who do most of their banking through computer-based online channels; and (iii) *digital adventurers* — customers who exclusively use mobile devices, wearable devices, and other digital channels[2]. Focusing on digital-savvy customers reflects customer-level strategic decisions of RBUs that consider online and digital customers their most critical customer segments. Prior studies on product innovation suggest that a firm's efforts in new product development depend, in part, upon the strategy they follow (Frambach et al., 2003). Studies on customer centricity argue that identifying the most valuable customers is critical since focusing on the 'right' customers provides strategic advantages to the firm over the other competitors (Fader, 2012). Market segmentation, targeting, and positioning have been studied and applied in the financial industry (Kaynak & Harcar, 2005).

[2] This segmentation was adopted based on consultations with industry experts and adapted from the global digital survey conducted by Deloitte (2018). Retail banking customers across the globe fall into these three distinct segments.

Previous studies tend to segment retail banking customers based on their demographics (e.g., age, gender, and income) (Kaynak & Harcar, 2005). However, given the increasing digital demand across all generations and the different behaviors between digital and non-digital customers, the traditional approach for market segmentation and positioning is insufficient for RBUs in today's digital age. A more concentrated marketing strategy is needed for RBUs to achieve better performance from digitizing and offering digital retail banking services.

In the context of the digitization of retail banking services, we propose that focusing on digital-savvy customers is important as digital-savvy customers are the ones who can bring the most value to RBUs. Digital-savvy customers have greater interests in digital retail banking services and show stronger and longer commitment to their banks (M. Xue et al., 2011). We posit that RBUs that focus on digital-savvy customers are more likely to enhance their capability to digitize retail banking services. RBUs that segment and focus on digital-savvy customers instead of traditional customers can gain a better understanding of their customers' digital preferences and needs, and therefore deliberately allocate needed resources to the digitization of retail banking services and thus strengthen their ability to digitize retail banking services in order to respond to such digital demands. RBUs that focus on digital-savvy customers are also highly motived to innovate and adapt to emerging digital technologies, thus, continually enhancing their ability to transform their existing retail banking services to the digital ones supported by emerging digital technologies. Since digital-savvy customers do most of their banking via online and mobile channels with little or no employee input, by targeting digital-savvy customers RBUs are more likely to advance their ability to convert existing face-to-face retail banking services to be offered digitally without human interactions.

This leads to Hypothesis 2:

Hypothesis 2. Focusing on digital-savvy customers is positively associated with the capability to digitize retail banking services.

3.3.3 Front-office back-office process and capability to digitize retail banking services

Front-office back-office process alignment (FOBO) refers to the extent to which the front-office and back-office processes (e.g., information sharing, problem solving) of RBUs are conducted in a synchronized manner when serving customers. Front-office back-office process alignment reflects the overall harmonization of the internal customer-serving process. *Front office* refers to the part of the enterprise that customers can see, experience, and interact with, while *Back Office* remains the part that is invisible to or insulated from customers (Johnston & Clark, 2005; Menor et al., 2002; Zomerdijk & De Vries, 2007). For service providers, it is critical that front-office and back-office "must function together as an integrated whole" (Menor et al., 2002, p. 145).

Previous studies on supply chain integration and new product development (NPD) find that a well-developed integration strategy (internal and external) is a key predictor of NPD success (Koufteros et al., 2005) and has a positive impact on product innovation capability (Schoenherr & Swink, 2015).

In the context of the digitization of retail banking services, aligning the front-office back-office process is an important internal effort for RBUs. We posit that, when the front-office back-office process of RBUs is increasingly aligned, the capability to digitize retail banking services can also be enhanced. By enhancing process synchronization, the front-office and back-office exchange information (e.g., customer data, goals, problems, and priorities) more frequently and operate as a team to solve problems. The more aligned processes help reduce the uncertainties in the digitization of retail banking services, enable RBUs to better understand their customers and existing service offerings, and keep up with the most recent digital technologies, thus, enhancing the ability of RBUs to continuously integrate digital technologies and transform existing retail banking services into digital ones that better serve the customers. The aligned front-office back-office process can also provide RBUs with first-mover advantages in determining what and how to digitize retail banking services, which leads to our next hypothesis:

Hypothesis 3. Front-office back-office process alignment is positively associated with the capability to digitize retail banking services.

3.3.4 Capability to digitize retail banking services as a mediator

Given the prior hypotheses, we further propose that the capability to digitize retail banking services serves as a mediator between (a) digital-savvy customer focus and business performance improvement and (b) front-office back-office process alignment and business performance improvement.

We propose that, in the context of digitization of retail banking services, focusing on digital-savvy customers and aligning front-office back-office process are key drivers for RBUs to elevate their capability to digitize retail banking services. From the strategy-performance perspective, in order to reach financial success, firms need to find customers who can bring the most value to the firm (Fader, 2012; Kumar & Petersen, 2005). The focus on digital-savvy customers is expected to motivate RBUs to digitize their existing face-to-face retail banking services; as such, RBUs may want to stay current with technological innovations and develop their ability to leverage emerging digital technologies to digitize their retail banking services. As a result, the digital retail banking services RBUs provide will also enable them to attract a larger customer base, achieve a greater market share of customers, and have a stronger market position.

From the operational efforts perspective, prior studies on supply chain integration and NPD show that product innovation capability (i.e., a firm's ability to develop innovative products) acts as a mediator between supply chain integration and firm performance (Schoenherr & Swink, 2015). In our context, the more aligned front-office back-office process allows RBUs to stay informed about customers' digital demands and concerns, thus, enabling RBUs to quickly and efficiently respond to customer needs by integrating relevant emerging digital technologies into retail banking services. Consequently, RBUs can be more flexible and less vulnerable when facing changing markets (e.g., the COVID-19 pandemic) and disruptions (e.g., technological disruption), thus, achieving greater improvement in business performance. Considering these, we present our next two hypotheses:

Hypothesis 4. Digital-savvy customer focus is indirectly and positively associated with the change in business performance through the capability to digitize retail banking services.

Hypothesis 5. Front-office back-office process alignment is indirectly and positively associated with the change in business performance through the capability to digitize retail banking services.

3.4 Research Methods

3.4.1 Relevant survey-based measures

Table A2.1 provides details regarding measures used to test our hypotheses, including measurement items and response anchors, whether a measurement scale is newly created or adapted from existing measures, and the relevant literature supporting these measures.

Business performance improvement (PERF) is measured with a newly-created, 5-item measurement scale, modelled after similar measurement scales from Vorhies and Morgan (2005), Vorhies et al. (2009), and Narayanan et al. (2011) for business performance and market effectiveness. Our five measurement items evaluate the improvement in various market performance metrics that one realizes from offering digital retail banking services to customers, including increases in customer base, increase in profitability, strengthening of competitive positioning, increase in market share, and decrease in operating cost, compared to their competitors. Each measurement item is paired with a 5-point Likert-response scale, anchored from 1 ("Much worse than competitors") to 5 ("Much better than competitors").

Capability to digitize retail banking services (CAP) is measured with a newly developed, 4-item measurement scale. The four measurement items assess the ability of RBUs to integrate and leverage emerging digital technologies (e.g., AI, mobile technology, cloud computing), to digitize existing retail banking services or to develop new digital retail banking services that are available digitally without physical (e.g., face-to-face) interactions and can be accessed and executed directly by customers without physical interactions. Each measurement item is paired with a 5-point Likert-response scale, anchored from 1 ("Very inaccurate") to 5 ("Very accurate"). We model the four measurement items after the "eBusiness Capability" measurement scale from Devaraj et al. (2007), which assesses the ability of a firm to use internet technologies to support online business transactions with customers and suppliers, and after the "IT Experience" measurement scale from Menor and Roth (2007), which assesses the use of IT to support or improve inter-organizational coordination when developing new services.

Front-office back-office process alignment (FOBO) is measured with a 4-item measurement scale that adapts one measurement item from the "Internal Integration" measurement scale in Schoenherr and Swink (2012), two from the "Internal Integration" measurement scale in Braunscheidel and Suresh (2009), and one from the "Process Integration" measurement scale in Narayanan et al. (2011). The four measurement items evaluate how well front-office and back-office processes within a retail bank or credit union work together when delivering retail banking services to customers, particularly regarding information sharing, problem solving, goals communication, and teamwork. Each item is paired with a 5-point Likert-response scale, anchored from 1 ("Strongly disagree") to 5 ("Strongly agree").

Digital-savvy Customer Focus (IMP_CUST) is measured based on the response indicating which customer segment (i.e., *traditionalist, online embracer, digital adventurer*) is most critical for RBUs. We propose that focusing on digital-savvy customers (i.e., *online embracers* and *digital adventurers*) acts as a key driver for RBUs to develop and enhance their capability to digitize their retail banking services. Furthermore, having a clear target of digital-savvy customers may also provide RBUs with greater motivation, willingness, and effort to the digitization and may gain greater improvement from offering digital retail banking services.

3.4.2 Objective performance measures

In this study, since we use self-reported survey data, our performance measure (business performance improvement, *PERF*) is perceptual in nature. Several survey studies have pointed out the limitations of using perceptual performance measures; for instance, Spanos and Lioukas (2001) argue that the respondents' perceptions may not represent the objective reality, thus, highlighting the necessity of using objective measures to alleviate the problem (de Koster et al., 2011; Fynes & De Búrca, 2005; Revilla & Knoppen, 2012, 2015; Spanos & Lioukas, 2001; Su &

Linderman, 2016). We, therefore, collected secondary data from RBUs' annual reports and examined our model by using two objective performance measures, ROA and ROE, which are important metrics commonly used in banking studies to measure banks' profitability with respect to equity or assets (e.g., Aebi et al., 2012). These two metrics reflect how the organization manages and generates income from these resources. Particularly, since our business performance improvement (PERF) measure is designed to capture performance improvement from offering digital retail banking services, the objective performance metrics are also measured in terms of improvement over time.

Change of ROA (CHN_ROA) is measured as the improvement of Return on Assets (ROA) from 2020 to 2021. ROA, a profitability ratio, reflects how well a firm performs with respect to its total assets and has been used as an accounting-based, objective financial performance measure in service operations studies (Menor & Roth, 2008; Narayanan et al., 2021). For instance, Menor and Roth (2008) used the ROA of retail banks as the business-level performance metric when examining the impact of new service development competence in retail banks. We also use the change of ROA (ΔROA) as the objective performance measure, whereas ROA is measured as a percentage of net income and average total assets: $ROA_{2021} = \frac{Net\ Income_{2021}}{Average\ Assets} = \frac{Net\ Income_{2020}}{(Assets_{2021}+Assets_{2020})/2}$, $ROA_{2020} = \frac{Net\ Income_{2020}}{Average\ Assets} = \frac{Net\ Income_{2020}}{(Assets_{2020}+Assets_{2019})/2}$) and the change of ROA is measured as the difference of ROA over one year, from 2020 to 2021: *change of ROA (CHN_ROA)* = $\Delta ROA\ = ROA_{2021} - ROA_{2020}$.

Change of ROE (CHN_ROE) is measured as the improvement of Return on Equity (ROE) from 2020 to 2021. ROE is another ratio measure that reflects the profitability of RBUs. Various studies (e.g., Yang et al., 2018) examine the impact of adopting e-banking on bank performance by using ROE as an objective financial measure. The change of ROE (ΔROE) is the objective performance measure, and ROE is measured as a percentage of net income and equity: $ROE_{2021} = \frac{Net\ Income_{2021}}{Equity_{2021}}, ROE_{2020} = \frac{Net\ Income_{2020}}{Equity_{2020}}$) and the change of ROE is the difference of ROE from 2019 to 2020: *change of ROE* **(CHN_ROE)** = $\Delta ROE\ = ROE_{2021} - ROE_{2020}$.

By including these two objective performance measures, the performance improvement from offering digital retail banking services is measured in three ways: one survey-based measure (*PERF*) and two objective performance measures (*CHN_ROA, CHN_ROE*). Since the objective performance measures are collected from archival sources and measured as temporally lagged data compared to our survey administration time, this procedure alleviates the concerns of common method bias due to the same sources or raters and eliminates the bias from effects such as consistency motifs, implicit theories, social desirability (Podsakoff et al., 2003).

3.4.3 Control variables

Additionally, we consider and include a set of variables at both the firm level and market level to control for the potential effects on the business performance of RBUs. We consider these control variables: retail banking unit type (i.e. an RBU is a retail bank or credit union), number of digital offerings, digitization age, established age, investment in digitization of service offerings, as well as market turbulence and technological turbulence at the market level to rule out the possible alternatives that may bias our results. Table A2.2 summarizes the details of these control variables.

Retail banking unit type (RBU_TYPE) is measured as a dummy variable, which represents the retail banking unit being analyzed as a retail bank or credit union. We control the type of retail banking unit due to the differences in the nature of RBUs. For instance, different objectives (for-profit vs. not-for-profit), regulation (federal vs. provincial), geographic restrictions (national vs. provincial or local), ownership (investors vs. members), and so on.

Number of digital offerings (D_OFFER) is measured as a count value based on the number of digital retail banking services being offered by a retail bank or credit union. A total of nine categories of digital retail banking services are listed: digital account management, digital financing, digital money, digital payment, digital investment, digital insurance, digital security, digital financial planning, and digital advice. The strategy literature suggests that diversification plays a critical role in influencing firm performance (Chakrabarti et al., 2007; Narasimhan & Kim, 2002; Palich et al., 2000) and such diversification generally refers to the number of different products a firm offers (L. Xue et al., 2013). Particularly, selective digitization is argued not to help conventional banks from meeting the increasing digital demands of customers or compete with Financial Technology (FinTech) innovators (Maiya, 2017). RBUs that offer a broader range of digital retail banking services are more likely to gain better performance from offering digital retail banking services to customers.

Digitization age (D_AGE) is measured based on the reported year that the RBUs offered their first digital retail banking services. The longer RBUs started their digitization, the more experience they likely gained and the greater improvement they likely obtained. Rather than considering the years of operation, we use the time RBUs first offered their digital retail banking services.

Established age (E_AGE) is measured based on the total number of years that the RBUs have been established. On the one hand, RBUs with a longer history may have more resources to work with when digitizing services and thus, may achieve better performance. On the other hand, since using emerging digital technologies may have conflicts with the existing IT systems RBUs have, long-established RBUs may encounter obstacles when updating or replacing their systems with digital technologies and thus, hinder progress.

Investment in the digitization of service offerings (INVEST), is based on the self-reported responses in our survey. Investment in the digitization of existing service offerings is categorized into three groups: low—investments less than CAN$100,000, medium—investments from CAN$100,000 to $5 million, and high—investments higher than CAN$5 million.

Market turbulence (MAR_TUR) is measured with a three-item measurement scale adapted from H. Liu et al. (2016). The three measurement items evaluate the pace of change in the customer base and customer preferences for retail banking services. Each item is paired with a 5-point Likert-response scale anchored from 1 ("Strongly disagree") to 5 ("Strongly agree").

Technology turbulence (TECH_TUR) is measured with a two-item measurement scale adapted from H. Liu et al. (2016). The two items evaluate the changes in new technologies used to support retail banking services. Each item is paired with a 5-point Likert-response scale anchored from 1 ("Strongly disagree") to 5 ("Strongly agree").

3.4.4 Sample and key informants

Our study focuses on the Canadian retail banking industry. The sampling frame identified 40 retail banks[3] and 230 credit unions operating across all Canadian provinces except for Quebec[4]. The 40 retail banks include 29 headquartered in Canada (i.e., those listed as domestic banks in Canada's Office of the Superintendent of Financial Institutions: osfi-bsif.gc.ca/) and 11 considered to be subsidiaries of non-Canadian banks (i.e., those listed as *foreign banks* in Canada's Office of the Superintendent of Financial Institutions). The listing of credit unions is compiled from directories maintained by the Credit Union Deposit Insurance Corporation of each province (excluding Quebec) (e.g., Credit Union Deposit Guarantee Alberta: cudgc.ab.ca, the Deposit Insurance Corporation of Ontario: dico.com). For each retail bank in the sampling frame, we first researched multiple sources (e.g., Nexis Uni, Investext, Hoovers, Mergent, and LinkedIn) to identify at least one key informant to whom the survey could be administered and collected their contact information. Various positions, including C-suites positions (CEO, CDO, CIO, etc.), VP, Director, and Manager, with experience in digital-related areas (e.g., digital banking, digital product management, technology and digital transformation, digital channels), were selected

[3] The list provided on OSFI-BSIF.GC.CA includes both Schedules I and II, but only 40 of them offer retail banking services.

[4] Credit unions in Quebec are excluded from the sampling list because all Quebec credit unions are federated by Desjardins whereas credit unions in the other provinces run independently.

based on their knowledge of digitization in their RBUs. The demographic information of the informant, such as job title, years of experience, age, gender, and education, were collected from the self-reported questionnaire.

3.4.5 Web-based survey administration

We designed a web-based survey for data collection. Included in the web-based survey are the measurement items from Table A2.1, as well as questions for relevant control variables and to gather demographic information. The same web-based survey was administered separately with one for retail banks and one for credit unions. The questions were designed to consider each RBU as the unit of analysis.

We implemented different strategies to administer the web-based survey. For retail banks, we first sent an email to all potential informants to ask for their "willingness to participate" and finalized one key informant from each retail bank. We then sent a formal invitation, with a direct link to our web-based survey, to the key informant who agreed to participate. For credit unions, we administered the web-based survey with support from the Canadian Credit Union Association (CCUA: ccua.com), the trade association to which Canadian credit unions belong. The CCUA directly contacted its credit union members and encouraged participation via internal communications. After three rounds of reminders from CCUA, we then followed up with the remaining credit unions that had not yet responded by directly sending an email to executives (e.g., CEO, general manager) with the web-based survey link embedded.

The informants were directed to click the embedded hyperlink in the invitation email, after which an introductory landing page would appear, containing details about the benefits of the survey, instructions for completing the survey, approximate time to complete the survey in one un-interrupted seating (~ 25 minutes), and a request to affirm informed consent. In this survey, measurement items constituting a measurement scale are displayed together on the same page of the survey, and items for different variables that are being tested in the conceptual model are placed in separate subsections

After five reminder emails, we achieved a 40% response rate for credit unions (N = 92) and an 80% response rate for retail banks (N = 32). The overall response rate for our sample is, therefore, 46% (Total N = 124). Table 3.1 summarizes demographic information about the sample and the corresponding key informants. We recognize that our sample size is small or moderate, thus limiting the types of statistical techniques (e.g., structural equation modelling, (SEM)) we can use in this study. A key reason is that the total number of retail banks and credit unions in Canada is limited, with a number of 270 RBUs in total. However, given that our study aims to examine a new and unexplored problem, ensuring our sample is *representative* and *free from nonresponse bias* is more important (Frohlich, 2002). Our response rate from retail banks is quite high, and our overall response rate from all RBUs is also adequate for survey studies in operations management (Frohlich, 2002). Additionally, as shown in Table 3.1, different types of RBUs have a reasonable number of representations in terms of type and size. We also address the concerns of non-response bias in the next section.

Table 3.1: Sample and Key Informant Demographics

	N = 124	Percentage (%)
Retail Banking Unit Type		
Retail Bank	32	25.8%
Credit Union	92	74.2%
Number of full-time employees		
< 50	44	35.5%
51–100	20	16.1%
101–500	38	30.6%
501–1000	11	8.9%
1001–5000	7	5.6%
> 5001	4	3.2%
Informant job title		
President & C-Suite	58	46.8%
Executive VP/VP	22	17.7%
Senior Director/Director	14	11.3%
Manager	25	20.2%
Other	5	4.0%
Informant years of working experience		
< 1 year	1	0.8%
1–5 years	39	31.5%
5–10 years	25	20.2%
10 –15 years	18	14.5%
> 15 years	41	33.1%

3.4.6 Non-response bias assessment

We designed the web-based survey following guidelines by Rogelberg and Stanton (2007) to minimize non-response bias. We implemented “design carefully” as a response facilitation technique by engaging a third party with expertise in designing and formatting the web-based survey to ensure it was easy to read and the questions carefully spaced. We implemented the “publicize the survey” response facilitation technique by explaining the purposes and benefits of the survey in the communication emails. To help increase the likelihood of completing the survey, we followed the “establish survey importance” technique by explaining to the informants how valuable their opinions are to this study. At the same time, we followed the "use reminder notes" response facilitation technique by sending multiple waves of reminders and also phoning informants directly after sending the surveys. Finally, we combined the response facilitation techniques of "provide incentives" and "provide survey feedback" by offering two exclusive executive reports, entitled "Digitization Journey Report" and "Digitizing Retail Banking Services: Opportunities, Challenges, and Realizable Benefits," upon completion.

In the post-data collection, we assessed potential non-response bias by conducting several tests using archival analysis and wave analysis as suggested by Rogelberg and Stanton (2007). For the archival analysis, we used the collected archival data to compare the responded to those that did not, and found no significant differences between the two groups in terms of total assets (*retail banks: t =1.665, p = 0.104; credit unions: t = 1.371, p = 0.173*), total deposits (*retail banks: t =1.622, p = 0.113; credit unions: t = 1.494, p = 0.137*), net income (*retail banks: t = 0.918, p = 0.364; credit unions: t = 1.370, p=0.173*), total land and building expense (*retail banks: t =1.662, p = 0.105; credit unions: t = 1.075 p = 0.286*), and computer and technology equipment expenses (*retail banks: t = 0.670, p = 0.507; credit unions: t = 1.631, p = 0.107*). For the wave analysis, we used the collected archival data to compare those who responded early (i.e., first 25%) to those that responded late (i.e., last 25%). Particularly, considering the small size of retail banks that responded early and late, we used the two-sample Fisher-Pitman Permutation test for the wave analysis, which detected no significant differences with respect to total assets (*retail banks: z = 0.640, p = 0.508; credit unions: t = -0.362, p = 0.721*), total deposits (*retail banks: z = 0.827, p= 0.408; credit unions: t = -0.202, p = 0.842*), net income (*retail banks: z = 0.594, p = 0.552; credit unions: t = -0.700, p = 0.491*), total land and building expenses (*retail banks: z = 0.638, p = 0.523; credit unions: t = 0.007, p = 0.994*), and computer and technology equipment expenses (*retail banks: z = 1.074, p = 0.283; credit unions: t = -0.848, p = 0.402*).

We also emailed or called the contacts at the retail banks and credit unions that declined to participate to check the reasons for non-participation. The main reasons stated for declining were either lack of time or concerns about confidential information. After screening the collected responses, 15 responses were discarded due to incorrect responses to the screening questions (e.g., retail banks and credit unions that offer digital offerings but selected "No" in the survey question: "Does your retail bank or credit union offer any digital retail banking services to customers?"). Eventually, we got a total of 109 usable responses.

3.4.7 Assessing measurement properties

To assess measurement quality, we checked for unidimensionality, reliability, convergent validity, and discriminant validity by conducting an exploratory factor analysis (EFA) first, followed by a confirmatory factor analysis (CFA). Based on the EFA results, we checked if any item had low factor loading. For the CFA, we fitted the measurement model shown in Figure 3.2 to the data. Table 3.2 shows the factor loading, standardized loading, t-values, goodness-of-fit indices, Cronbach's alpha, composite reliability, and AVE.

Figure 3.2: Measurement Model

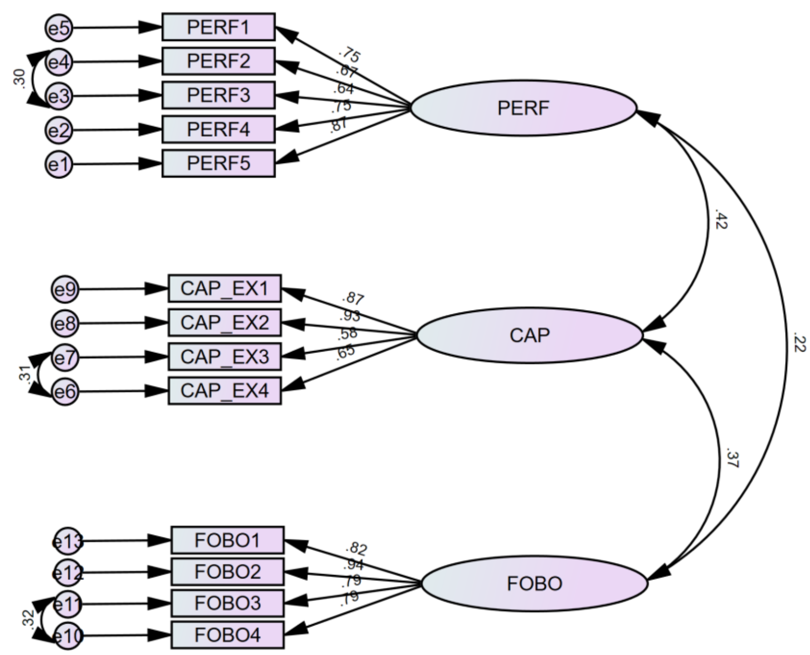


Table 3.2: Constructs Reliability and Validity Analysis

Constructs and items	Factor loading	Standardized loading	S.E.	t-value	Reliability and Validity
Capability to Digitize Retail Banking Services (CAP)					
CAP1	1.37	0.87	0.19	7.43	Cronbach's alpha = 0.85, Composite
CAP2	1.42	0.93	0.19	7.52	reliability = 0.85, AVE =0.60,
CAP3	0.92	0.58	0.14	6.48	Goodness-of-fit indices: $\chi^2 = 10.96$,
CAP4	1.00	0.65	--	--	df = 2, CFI = 0.958, IFI = 0.959,
					TLI = 0.873, SRMR = 0.056
Business Performance Improvement (PERF)					
PERF1	0.92	0.75	0.11	8.45	Cronbach's alpha = 0.86, Composite

PERF2	0.61	0.67	0.08	7.28	reliability = 0.86, AVE = 0.56,
PERF3	0.66	0.64	0.10	6.89	Goodness-of-fit indices: χ2 = 15.25,
PERF4	0.81	0.75	0.10	8.44	df = 5, CFI = 0.956, IFI = 0.957,
PERF5	1.00	0.87	--	--	TLI = 0.938, SRMR = 0.045
Front-office Back-office Process Alignment (FOBO)					
FOBO1	1.21	0.82	0.13	9.46	Cronbach's alpha = 0.91, Composite
FOBO2	1.40	0.94	0.13	10.49	reliability = 0.90, AVE = 0.70,
FOBO3	1.10	0.79	0.10	11.00	Goodness-of-fit indices: χ2 = 8.98,
FOBO4	1.00	0.79	--	--	df = 2, CFI = 0.976; IFI = 0.977,
					TLI = 0.970, SRMR = 0.028

For unidimensionality, we conducted a CFA for each construct to examine whether a set of indicators reflect one (vs. more than one) underlying factor. We checked the model-of-fit indices for each construct. As shown in Table 3.3, a good model fit suggests all the constructs are unidimensional (Hu & Bentler, 1999). Further, we conducted a confirmatory factor analysis with three factors and checked the overall model-of-fit indices. The oblique CFA model shows that $\chi^2 = 86.27$, df = 59, $p = 0.012$; CFI = 0.966, GFI = 0.901, IFI = 0.966, TLI = 0.955; SRMR = 0.06, RMSEA = 0.065, with $p = 0.195$ and 90% confidence interval for RMSEA = (0.032, 0.094). A good model-of-fit further ensures unidimensionality.

For reliability, we assessed it using Cronbach’s alpha and composite reliability. All the constructs show the value of Cronbach’s alpha and composite reliability are greater than 0.8, which suggests an acceptable level of reliability (Lance et al., 2006).

For convergent validity, we evaluated the convergent validity of each measurement scale by checking all item loadings from the CFA. The items of a specific construct should converge and share a high proportion of variance in common. As shown in Table 3.3, the item loadings sizes are high, ranging from 0.58 to 0.93, with significant t-values greater than 2, suggesting convergent validity. Additionally, the average variance extracted (AVE) for each construct also exceeds 0.5, which further suggests convergent validity (Koufteros, 1999).

For discriminant validity, we compared AVE for all constructs with the shared variance among constructs (i.e., the variance of the correlations of each pair of constructs) (Koufteros, 1999). For each construct, AVE is higher than the shared variance among constructs, which suggests a satisfactory level of discriminant validity. We also compared models between unconstrainted models (i.e., allows paired constructs to correlate freely) and constrained models (i.e., sets correlation of paired constructs equal to 1) for all pairs of constructs and summarized the chi-square, df, and the chi-square differences. All the chi-square differences are significant, suggesting discriminant validity (Bagozzi et al., 1991; Venkatraman, 1989).

Table 3.3: Discriminant Validity Analysis

Construct Pairs	Unconstrained		Constrained		Diff Test	
	X^2	df	X^2	df	ΔX^2	p-value
CAP and PERF	58.559	28	216.681	29	158.122	0.000
CAP and FOBO	57.293	21	235.708	22	178.415	0.000
FOBO and PERF	58.577	26	110.281	27	51.704	0.000

3.4.8 Common method bias

We designed the web-based survey to mitigate common method bias. Following the advice of Podsakoff et al. (2003), we identified the potential sources of common method biases and controlled them using the suggested techniques and procedures. First, we included the "Informed Consent Form" at the beginning of the survey, which assured informant anonymity and confidentiality and reduced the social desirability effects. Second, we carefully checked all the construct items to avoid ambiguity and clearly provided instructions and relevant definitions to informants to minimize the evaluation apprehension. We also used different scale anchors (e.g., *strongly disagree–strongly agree, very inaccurate–very accurate, much worse–much better than competitors*) and different formats (e.g., 5-point and 7-point Likert scales) in the web-based survey. Third, we placed different variables related to the conceptual model into separate subsections. Finally, secondary data about performance measures (i.e., ROA, ROE) were also collected from the annual reports and used as objective performance measures.

In the post-data collection, we conducted two tests to assess common method bias. First, we conducted Harman's single-factor test to detect whether there is a single factor that accounts for the majority of the covariance among all dependent and independent variables. We entered all items of the related constructs (i.e., capability to digitize retail banking services, business performance improvement, and front-office back-office processes alignment) into an EFA and examined the unrotated factor solution with all distinct factors' eigenvalues greater than 1. The first factor accounts for 34.11% of the total variance, suggesting no serious issue from the common method. Second, we followed Lindell and Whitney (2001) to perform the partial correlation procedure. Instead of leveraging a theoretically unrelated variable similar to Kim (2014) and H. Liu et al. (2016), we followed the modified test in Pavlou et al. (2007) to partial out the second smallest correlation as a "marker" variable. Then we compared the results of correlation before and after controlling the common method variance (CMV) "marker". The results show that all correlations among constructs remain significant, which indicates that common method bias is not a major concern in this study.

3.5 Analysis and Results

3.5.1 Results using seemingly unrelated regression results

After assessing the measurement model, we obtained the factor scores for PERF, CAP, and FOBO based on the factor loadings in the measurement model. The objective performance measures, i.e., CHN_ROA and CHN_ROE, were measured using collected secondary data. Due to the unavailability of annual reports for some RBUs in both 2020 and 2021, the sample sizes for the analyses are different. Additionally, since analyses with small samples are sensitive to extreme values (Aguinis et al., 2013), we followed the outlier identification approaches summarized in Aguinis et al. (2013) and removed outliers before moving to the formal analyses[5]. Table 3.4 summarizes the descriptive statistics and correlations.

We first ran the analysis with the capability to digitize retail banking services (CAP) and all control variables, including the retail banking unit type (RBU_TYPE), number of digital offerings (D_OFFER), digitization age (D_AGE), established age (E_AGE), investment (INVEST), market turbulence (MAR_TUR), and technology turbulence (TECH_TUR). The multicollinearity was also checked using VIF values.

The model presented in Fig. 1 can be expressed using the following equations.

$$CAP = \beta_0 + \beta_1 * IMP\_CUST + \beta_2 * FOBO + \varepsilon_{CAP} \quad \text{(Eq. 3.1)}$$

$$PERF = \gamma_0 + \gamma_1 * CAP + \gamma_2 * RBU\_TYPE + \gamma_3 * D\_OFFER + \gamma_4 * E\_AGE + \gamma_5 * D\_AGE + \gamma_6 * INVEST + \gamma_7 * TECH\_TUR + \gamma_8 * MAR\_TUR + \varepsilon_{PERF} \quad \text{(Eq. 3.2a)}$$

$$CHN\_ROA = \gamma_0 + \gamma_1 * CAP + \gamma_2 * RBU\_TYPE + \gamma_3 * D\_OFFER + \gamma_4 * E\_AGE + \gamma_5 * D\_AGE + \gamma_6 * INVEST + \gamma_7 * TECH\_TUR + \gamma_8 * MAR\_TUR + \varepsilon_{CHN\_ROA} \quad \text{(Eq. 3.2b)}$$

$$CHN\_ROE = \gamma_0 + \gamma_1 * CAP + \gamma_2 * RBU\_TYPE + \gamma_3 * D\_OFFER + \gamma_4 * E\_AGE + \gamma_5 * D\_AGE + \gamma_6 * INVEST + \gamma_7 * TECH\_TUR + \gamma_8 * MAR\_TUR + \varepsilon_{CHN\_ROE} \quad \text{(Eq. 3.2c)}$$

In these equations, the capability to digitize retail banking services (CAP) is the dependent variable in Eq. 3.1 but also the independent variable in Eq. 3.2 (a, b, and c). Paxton et al. (2012) summarize how simultaneous equations can be addressed using the SEM with latent variables

[5] We followed the outlier identification techniques (e.g., box plot, standardized residual, studentized residual, Cook's D) suggested in Aguinis et al. (2013) and removed extreme values with standardized residual values greater than 3 and Cook's D values greater than 4/N.

Table 3.4: Descriptive statistics and correlation

Variable	Mean	SD	N	PERF	CHN_ROA	CHN_ROE	CAP	IMP_CUST	FOBO	RBU_TYPE	D_OFFER	E_AGE	D_AGE	INVEST	TECH_TUR
PERF	2.78	0.74	109												
CHN_ROA	0.14	0.30	91	0.11											
CHN_ROE	2.52	4.01	90	0.27	0.79 ***										
CAP	2.53	0.68	109	0.46 ***	0.17 *	0.23 **									
IMP_CUST	0.71	0.46	109	0.34 ***	0.15	0.17	0.24 **								
FOBO	2.88	0.63	109	0.24 **	0.13	0.08	0.40 ***	0.07							
RBU_TYPE	0.75	0.44	109	-0.26 ***	-0.34 ***	-0.28 ***	-0.14	-0.04	0.06						
D_OFFER	3.80	1.70	109	0.34 ***	0.13	0.19 *	0.28 ***	0.19 *	0.07	-0.04					
E_AGE	55.94	36.06	109	0.08	-0.07	-0.03	-0.04	-0.07	0.06	0.23 **	0.18 *				
D_AGE	0.47	0.51	109	-0.01	-0.23 **	-0.11	-0.04	0.04	0.18 *	0.11	0.16	0.15			
INVEST	2.01	0.61	109	0.21 **	0.21 **	0.30 ***	0.14	0.15	0.07	-0.24 **	0.30 ***	0.11	0.17		
TECH_TUR	3.86	1.07	109	-0.01	-0.13	0.01	0.12	-0.1	-0.12	0.03	-0.01	0.11	-0.09	0.03	
MAR_TUB	5.15	1.35	109	-0.07	0.06	0.10	-0.01	-0.02	-0.01	-0.05	-0.05	-0.08	0.01	-0.03	0.44 ***

*** p<0.01, ** p<0.05, * p<0.10

(e.g., Bollen, 1989) as well as simultaneous equations models (e.g., Greene, 2003) from the econometric tradition.

To test our hypotheses, we conducted seemingly unrelated regressions (SUR) using STATA in this study. We decided to use SUR because 1) the moderate sample size (N = 109) prevented us from conducting a full SEM with both the measurement model and structural model included together. Although path analysis has been used as an alternative in previous operation management studies with small and moderate sample sizes (e.g., Aranda, 2003; Carbonell et al., 2009; de Koster et al., 2011; Feger, 2014; N. Kim et al., 2013; Pullman et al., 2009; Revilla & Knoppen, 2012, 2015; Rosenzweig & Roth, 2004; Spanos & Lioukas, 2001), path analysis has more restrictive assumptions, including uncorrelated error terms (disturbance terms) (Foster et al., 2011). However, prior studies on testing for mediations have pointed out that uncorrelated error terms (i.e., ε_{CAP} and ε_{PERF}) is a key assumption (e.g., Preacher & Hayes, 2008; Rungtusanatham et al., 2014). Such assumptions have been ignored or assumed to be accepted in many studies (DeVaro & Boyd, 2016; Shaver, 2005). Since the error term is "thought of as latent variables that capture the aggregate effect of all the sources of variance aside from the ones modeled by the research" (Ketokivi & McIntosh, 2017, p. 11), it could capture unexplained/unobserved variables and measurement error. Shaver (2005) pointed out the likelihood that "the existence of measurement error and missing variables can lead to the correlation of error terms across regression equations" (p. 331). If error terms are correlated, the assumption in the testing for mediating variables will be violated, and the use of path analysis and/or SEM will result in biased and inconsistent estimations. Thus, we decided not to use path analysis or SEM in this study.

Second, SUR, introduced by Zellner (1962), is an econometric modelling technique that also enables researchers to simultaneously assess a system of equations in which variables presented as the dependent variable in one equation can be an independent variable in another (Greene, 2003). SUR is used as a solution for path analysis with correlated errors (Beasley, 2008) and is considered to be equivalent to ordinary least squares (OLS) when the right-hand side of the equations are exactly the same set of variables and/or the error terms are uncorrelated. However, SUR is more efficient than OLS when including different sets of variables and/or with the possibility of correlated error terms across equations (Ataseven et al., 2018). Additionally, SUR has been used in recent operations management studies, such as Ataseven et al. (2018), and Narayanan et al. (2021), and scholars have argued that SUR offers several advantages: (a) it enables simultaneous evaluation with both latent and observed variables (Preacher et al., 2007),

(b) it is effective for estimating mediations with cross-sectional data (Greene, 2003), (c) it alleviates endogeneity concerns when a variable is the dependent variable in one equation but also independent in another, and most importantly, (d) it considers the possible correlated error terms (Autry et al., 2010; Autry & Golicic, 2010). Specifically, in the study of Ataseven et al. (2018), a moderate sample size (N = 110) limited their use of SEM so they used SUR as the main analysis method. They argued that SUR has advantages over other methods such as path analysis due to its consideration of cross-equation error correlations.

Using SUR assumes that error terms are homoscedastic. We tested the assumption using the Breusch-Pagan (BP) test. The nonsignificant *p*-value (shown in the results) suggests that heteroscedasticity is absent and that the errors contain constant variance. We presented the SUR results in Table 3.5, in which factor scores are used for each latent variable; the results for each performance improvement measurement (i.e., PERF, CHN_ROA, and CHN_ROE) are listed side by side in Models 1 to 3.[6]

We then checked the results for each hypothesis. First, the effect of the capability to digitize retail banking services (CAP) on business performance improvement (PERF) is positive and significant in all three models (Model 1: $b = 0.486, p < 0.001;$ Model 2: $b = 0.074, p = 0.094;$ Model 3: $b = 0.994, p = 0.100$), which suggests that Hypothesis 1 is supported. Second, the effect of focusing on digital-savvy customers (i.e., the digital-savvy customer as the most important customer segment, IMP_CUST) on the capability to digitize retail banking services (CAP) is positive and significant in all three models (Model 1: $b = 0.352, p = 0.006;$ Model 2: $b = 0.318, p = 0.011;$ Model 3: $b = 0.319, p = 0.018$), which supports Hypothesis 2. Third, the effect of front-office back-office process alignment (FOBO) on the capability to digitize retail banking services (CAP) was positive and significant in all three models (Model 1: $b = 0.423, p < 0.001;$ Model 2: $b = 0.506, p < 0.001;$ Model 3: $b = 0.436, p < 0.001$), which supports Hypothesis 3.

Table 3.5: Seemingly unrelated regression results

	Model 1		**Model 2**		**Model 3**	
	Eq (1)	Eq (2)	Eq (1)	Eq (2)	Eq (1)	Eq (2)

[6] We conducted additional analyses for PERF. First, we ran an analysis using average scores for our variables and found that all hypotheses were supported. Second, we ran an analysis using the single performance indicator as DV for Eq. 3.2a. PERF_i includes an increase in customer base (PERF_1), an increase in profitability (PERF_2), a decrease in operating costs (PERF_3), the strengthening of competitive positioning (PERF_4), and an increase in market share (PERF_5). Identical results were obtained with all hypotheses supported for each of the single-factor performance measures.

	DV = CAP	DV = PERF	DV = CAP	DV = CHN_ROA	DV = CAP	DV = CHN_ROE
Independent Variables						
IMP_CUST	0.352 ***		0.318 **		0.319 **	
	(0.006)		(0.011)		(0.018)	
FOBO	0.423 ***		0.506 ***		0.436 ***	
	(<0.001)		(<0.001)		(<0.001)	
CAP		0.486 ***		0.074 *		0.994 *
		(<0.001)		(0.094)		(0.100)
Control Variables						
RBU_TYPE		-0.371 **		-0.177 ***		-1.527 *
		(0.011)		(0.007)		(0.086)
D_OFFER		0.081 **		0.016		0.278
		(0.030)		(0.339)		(0.233)
E_AGE		0.002		-0.001		-0.001
		(0.178)		(0.789)		(0.896)
D_AGE		-0.042		-0.151 ***		-1.072
		(0.732)		(0.008)		(0.171)
INVEST		0.045		0.089 *		1.671 **
		(0.673)		(0.073)		(0.018)
TECH_TUR		-0.025		-0.064 **		-0.309
		(0.684)		(0.031)		(0.451)
MAR_TUR		-0.023		0.031		0.427
		(0.639)		(0.143)		(0.170)
Constant	1.058 ***	1.534 ***	0.897 ***	0.014	1.200 ***	-3.970
	(<0.001)	(<0.001)	(<0.001)	(0.944)	(<0.001)	(0.147)
R^2	0.2071	0.3115	0.2910	0.2494	0.2298	0.2075
F	30.64 ***	62.27 ***	38.32 ***	33.98 ***	26.90 ***	24.36 ***
N	109		91		90	
Breusch-Pagan test	0.3131		0.4605		0.8637	

Note: Sample sizes are different due to the availability of secondary data. Estimates are shown in the table together with *p*-value in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

To test the significance of indirect effects, we conducted the bootstrapping method with 5,000 replications. This approach has also been used by Ataseven et al. (2018) and Narayanan et al.

(2021), in which they conducted SUR first, followed by the bootstrapping approach to test indirect effects. To achieve the most accurate results, we assessed the magnitude and significance of each indirect effect by bootstrapping the estimates without the insignificant control variables. We adapted the indirect effect of bootstrapping from Preacher and Hayes (2008) and Hayes (2013). We then implemented the analysis in STATA and presented the results in Table 3.6. First, the indirect effect of IMP_CUST on PERF via CAP (expressed using parameter a_1*b) is positive and significant in all three models at a 90% bias-corrected CI (Model 1: $a_1*b = 0.169$ *with 90% bias-corrected CI = [0.057, 0.331];* Model 2: $a_1*b = 0.027$ *with 90% bias-corrected CI = [0.003, 0.080];* Model 3: $a_1*b = 0.359$ *with 90% bias-corrected CI = [0.031, 1.091]*), which supports Hypotheses 4. Second, the indirect effect of FOBO on PERF via CAP (expressed using parameter a_2*b) is also positive and significant in in all three models at a 90% bias-corrected CI (Model 1 ($a_2*b = 0.203$ *with 90% bias-corrected CI = [0.107, 0.326]*) and Model 2 ($a_2*b = 0.043$ *with 90% bias-corrected CI = [0.005, 0.101];* Model 3 ($a_2*b = 0.491$ *with 90% bias-corrected CI = [0.053, 1.083]*).

Table 3.6: Indirect effect results using bootstrapping with 90%, 95%, 99% bias-corrected CI

Model 1: Eq (1) DV = CAP, Eq (2) DV = PERF

Indirect Effect	Estimates	Boot SE	90% bias-corrected CI	95% bias-corrected CI	99% bias-corrected CI
IMP_CUST	0.169	0.08	(0.057, 0.331)	(0.038, 0.368)	(0.007, 0.445)
FOBO	0.203	0.07	(0.107, 0.326)	(0.093, 0.350)	(0.057, 0.408)

Model 2*: Eq (1) DV = CAP, Eq (2) DV = CHN_ROA

Indirect Effect	Estimates	Boot SE	90% bias-corrected CI	95% bias-corrected CI	99% bias-corrected CI
IMP_CUST	0.027	0.022	(0.003, 0.080)	(-0.001, 0.092)	(-0.009, 0.112)
FOBO	0.043	0.12	(0.005, 0.101)	(-0.001, 0.115)	(-0.017, 0.138)

Model 3*: Eq (1) DV = CAP, Eq (2) DV = CHN_ROE

Indirect Effect	Estimates	Boot SE	90% bias-corrected CI	95% bias-corrected CI	99% bias-corrected CI
IMP_CUST	0.359	0.31	(0.031, 1.091)	(-0.009, 1.253)	(-0.129, 1.640)
FOBO	0.491	0.31	(0.053, 1.083)	(-0.028, 1.198)	(-0.207, 1.490)

Note: Sample sizes are different due to the availability of secondary data. Model 1: N = 109; Model 2: N = 91; Model 3: N = 90. The 90%, 95%, and 99% bias-corrected CI is based on 5,000 bootstraps.

We further conducted a contrasts comparison of these two indirect effects. Previously, MacKinnon (2000) described methods to test contrasts among indirect effects with multiple mediator models to check whether certain mechanism(s) (i.e., mediators) would create stronger impacts than the others. Based on the estimates in the mediation results, MacKinnon (2000) estimated the variance of the difference between two indirect effects and set up a 95% confidence interval to determine the significance. In this study, we want to further identify which indirect effect or exogenous variable (IMP_CUST or FOBO) has a greater impact on business performance improvement (PERF) via the capability to digitize retail banking services (CAP).

Here, two indirect effects (a_1*b and a_2*b) via CAP were estimated and tested. Based on the results, and since both indirect effects have the same positive sign, we defined and tested the difference between the two indirect effects. The difference between two indirect effects can be expressed as $a_1 * b - a_2 * b$. While it is easy to capture the difference, it is difficult to estimate the standard error of the difference and ensure the assumption of a normal sampling distribution. The bootstrapping method used to test for mediation effects also offers advantages when testing for contrasts among specific indirect effects (Preacher & Hayes, 2008; Rungtusanatham et al., 2014). Therefore, we conduct inference for the difference between two indirect effects by again using the bootstrapping method. Particularly, we estimate the difference in each bootstrap and construct the bias-corrected confidence interval for the difference. The null hypothesis for the difference is H0: $a_1 * b - a_2 * b = 0$. The results, as shown in Table 3.7, show that in all three models, the difference between the two indirect effects is not significantly different than zero.

Table 3.7: Indirect effects contrasts using bootstrapping with 90%, 95%, 99% bias-corrected CI

Model	N	Difference	Boot SE	90% bias-corrected CI	95% bias-corrected CI	99% bias-corrected CI
Model 1	109	-0.034	0.087	(-0.172, 0.119)	(-0.194, 0.153)	(-0.256, 0.223)
Model 2	91	-0.157	0.019	(-0.072, 0.002)	(-0.084, 0.004)	(-0.102, 0.157)
Model 3	90	-0.131	0.241	(-0.709, 0.112)	(-0.847, 0.208)	(-1.147, 0.399)

Note: Sample sizes are different due to the availability of secondary data. Model 1: N = 109; Model 2: N = 91; Model 3: N = 90. The 90%, 95%, and 99% bias-corrected CI is based on 5,000 bootstraps.

3.5.2 Endogeneity

For the endogeneity concerns, we first considered the endogeneity issues due to omitted variables. Confounding variables may exist that correlate with both dependent and independent variables but were not included in the study as omitted variables. To minimize the endogeneity concerns arising from omitted variables, we considered and included several control variables to account for the unmodeled effects (Lu et al., 2018). Furthermore, Busenbark et al. (2021)

reviewed studies in the management field and demonstrated the use of the impact threshold of a confounding variable (ITCV) to empirically evaluate the effects due to omitted variables. The ITCV is a single-value threshold that reflects the minimum correlations needed for omitted variables to invalidate the estimation between the independent and dependent variables (Frank et al., 2013). Busenbark et al. (2021) argue that higher ITCV scores indicate no major concerns due to omitted variables. We followed the instructions in Busenbark et al. (2021) and conducted an ITCV analysis using the *konfound* package in R (Frank et al., 2013).

We conducted regression analyses using Eq. 3.1 and Eq. 3.2a as presented earlier in section 5.1.1. We then conducted the ITCV analysis only for the statistically significant relationship. For Eq. 3.1, IMP_CUST and FOBO are significant, and for Eq. 3.2, CAP is significant. Table 3.8 summarizes these ITCV results.

Omitted variables can influence the relationship between the dependent and independent variables. The estimated relationship, β, between the dependent and independent variables in the presence of omitted variables consists of both (a) the accurate correlation between the dependent and independent variables and (b) the confounding correlation between the omitted variables and dependent and/or independent variables. The ITCV analysis thus provided an ITCV score and omitted variable correlations to determine to what extent the omitted variables would invalidate the inference between the dependent and independent variables. From the results for DV = CAP, we can see that (1) for an omitted variable to invalidate the inference of the digital-oriented customer focus (IMP_CUST) on the capability to digitize retail banking services (CAP), 33.6% of the estimates (i.e., 38 observations with zero effects) would have to be due to bias and such an omitted variable must be correlated at a minimum of 0.303 with both IMP_CUST and CAP; (2) for an omitted variable to invalidate the inference of front-office back-office process alignment (FOBO) on the capability to digitize retail banking services (CAP), 62.8% of the estimates (i.e., 68 observations with zero effects) would have to be due to bias and such an omitted variable must be correlated at a minimum of 0.535 with both FOBO and CAP. From the results for DV = PERF, for an omitted variable to invalidate the inference of capability to digitize retail banking services (CAP) on business performance improvement (PERF), 69.2% of the estimates (i.e., 75 observations with zero effects) would have to be due to bias and such an omitted variable must be correlated at a minimum of 0.603 with both CAP and PERF. We then checked the control variables to verify whether any control variables in our study had a higher correlation than these suggested minimum correlations and found no control variables showed higher correlations than the omitted variable correlations. Thus, overall, we believe that it is unlikely for omitted variables to invalidate our findings.

Table 3.8: ITCV analysis results

	Variable	% bias to change inference	number of observations with zero effects to change inference	omitted variable correlation	ITCV
DV = CAP	IMP_CUST	33.60%	37	0.303	0.092
	FOBO	62.80%	68	0.535	0.286
DV = PERF	CAP	69.20%	75	0.603	0.363

Note: α = 0.10 used in the analysis.

Second, since we leveraged mainly cross-sectional survey data (rather than longitudinal data), the data may involve potential endogeneity concerns because variables are measured contemporaneously. Particularly, the direction of the effects may be reversed and/or simultaneous. First, from the model-specification perspective, we argue that it is unlikely that the relationship between the capability to digitize retail banking services and business performance improvement is reverse or simultaneous. Several studies have already examined the impact of a firm's ability to use technologies in operations (e.g., "IT-enabled retail channel integration capability" in Oh et al. (2012)) on firm performance. An industry study (Westerman, Bonnet, and McAfee, 2014) also found that firms with stronger digital capabilities outperform others in various performance metrics in every industry (e.g., banking, retail, and telecom). Second, the endogeneity issue may exist concerning the relationship between front-office back-office process alignment and the capability to digitize retail banking services. Particularly, the front-office back-office process alignment (FOBO) may be endogenously affected by the capability to digitize retail banking services (CAP).

Rutz and Watson (2019) reviewed different approaches to address endogeneity issues, such as the instrumental variable (IV) approach, and the IV free approaches including the latent instrumental variable approach and the Gaussian copula approach, to test and address endogeneity concerns. Given the difficulties of finding strong instrument variables that would meet the theoretical and statistical conditions, this study leveraged the IV-free approaches, namely, the Gaussian copula approach (Park & Gupta, 2012) and the higher-moments approach (Lewbel, 1997) to evaluate the potential endogeneity issue. We conducted analyses using the *REndo* Package in R.

First, we conducted the Gaussian copula approach (Park & Gupta, 2012). Before running the analysis, we verified that the variables met the assumptions of the Gaussian copula approach (Park & Gupta, 2012). For each variable, the Kolmogorov-Smirnov tests showed a significant *p*-value ($p < 0.001$), which suggests that the variables met the non-normal distribution requirements and thus we proceeded with the Gaussian copula analysis.

Table 3.9 summarizes the results from the Gaussian copula approach. We obtained 90% bootstrap confidence intervals in the Gaussian copula approach based on the bootstrapping method with 10,000 bootstraps.

Table 3.9: Gaussian copula approach results (DV = CAP)

Variable	Estimate	Boots SE	90% CI
IMP_CUST	0.419	0.175	(0.046, 0.845)
FOBO	0.390	0.245	(0.131, 0.705)

Second, we conducted the higher-moments approach (Lewbel, 1997), which leveraged the internal instruments generated from the transformation of existing variables. This approach also enabled us to check several tests regarding the instruments and endogeneity assumptions. We then ran the higher moments approach with an internal instrument built from the potential endogenous variable (FOBO) using the transformation of $p2$ (i.e., $(Pi - \bar{P})^2$). The results, presented in Table 3.10, show that (a) the weak-instruments test from the higher-moments approach is significant ($p < 0.001$), which suggests that the internal instrument used in the higher moments approach is not weak; (b) the endogeneity test shows that the Durbin-Wu-Hausan test was non-significant ($p\text{-}value = 0.405$), which indicates that the suspected endogenous variable (FOBO) is actually exogenous.

Table 3.10: The higher-moments approach results (DV = CAP)

Variable	Coeff	Std. Error	*t*-value	*p*-value
IMP_CUST	0.314 **	0.131	2.390	0.018
FOBO	0.530 ***	0.164	3.225	0.001

(1) Weak instrument test (H0: the IV is weak): *p*-value < 0.001.

(2) Durbin-Wu-Hausman test (H0: the suspected endogenous variable is exogenous): *p*-value = 0.405.

The results from the IV-free approaches are also consistent with our previous findings summarized in section 5.1. We therefore argue that the endogeneity issue is not a major concern in our study and that our analysis is robust.

3.5.3 Robustness checks

To check the robustness of our results, we conducted an additional analysis using the alternative estimation method. Particularly, given the need to evaluate simultaneous equations and the concern of correlated error terms, we leveraged the three-stage least squares (3SLS) estimation as an alternative estimation method.

The 3SLS is a combination of SUR and 2SLS. Given that CAP is an endogenous variable in Eq. 3.1 but is also an exogenous variable in Eq. 3.2 (a, b, and c), 3SLS is suggested for use in such triangular structural models (Lahiri & Schmidt, 1978). Additionally, 3SLS can be used when there is the possibility of correlated error terms. Studies, for example, Shaver (2005), recommend using 2SLS to compensate for the issue of correlated error terms. Further, DeVaro and Boyd (2016) review the strategic management literature and suggest using 3SLS to obtain more precise estimations. Compared to 2SLS, 3SLS is argued to be more efficient and robust (Greene, 2003). In particular, recent operations management studies, such as Pu et al. (2019), also used the 3SLS estimation together with bootstrapping to analyze mediation effects. They argued that the 3SLS estimation could also accommodate the problem of correlated error terms and that it could be more robust than SEM when there are omitted paths.

Given the possibility of correlated error terms in Eq. 3.1 and Eqs. 3.2, we needed the mediator variable, CAP, in Eqs. 3.2 so that it does not contain the correlated error term that may be highly correlated with CAP. A possible candidate for the instrument is the exogenous variables, IMP_CUST and FOBO used in Eq (1). . As such, we had to run the analysis for Eq (1), get the predicted value for CAP (i.e., $\widehat{CAP}$), and replace CAP with the $\widehat{CAP}$ in Eqs. 3.2. We then had to run the SUR analysis including both equations. These analyses can be completed using 3SLS (a combination of 2SLS and SUR) without having to include external instrument variables. Eq. 3.1 and Eqs. 3.3 (use PERF as an example) along with the predicted value of CAP are as follows:

$$CAP = \beta_0 + \beta_1 * IMP\_CUST + \beta_2 * FOBO + \varepsilon_{CAP} \quad \text{(Eq. 3.1)}$$

$$PERF = \gamma_0 + \gamma_1 * \widehat{CAP} + \gamma_2 * RBU\_TYPE + \gamma_3 * D\_OFFER + \gamma_4 * E\_AGE + \gamma_5 * D\_AGE + \gamma_6 * INVEST + \gamma_7 * TECH\_TUR + \gamma_8 * MAR\_TUR + \varepsilon_{PERF} \quad \text{(Eq. 3.3)}$$

We, therefore, applied a 3SLS approach without instruments as robustness checks. The analysis was performed in STATA. The results are summarized in Tables 3.11 and 3.12. For results listed in Model 1 (DV = PERF) and 2 (DV = CHN_ROA): (i) Hypotheses 1 to 3 are supported, which are consistent with our previous results presented in section 5.1; (ii) Hypothesis 4, i.e., the indirect effect of IMP_CUST on PERF or CHN_ROA via CAP, is positive and significant at a 90% bias-corrected CI (Model 1: *a_1*b = 0.306 with 90% bias-corrected CI = [0.107, 0.569];* Model 2: *a_1*b = 0.053 with 90% bias-corrected CI = [0.005, 0.143])*, thus, supporting Hypothesis 4; (iii) Hypothesis 5, i.e., the indirect effect of FOBO on PERF or CHN_ROA via CAP, is positive and significant at a 90% bias-corrected CI (Model 1: *a_1*b = 0.302 with 90% bias-corrected CI = [0.107, 0.569];* Model 2: *a_1*b = 0.081 with 90% bias-corrected CI = [0.013, 0.185])*, thus, supporting Hypothesis 5. However, we also note that, for results presented in Model 3 when DV is CHN_ROE, only Hypotheses 1 and 2 are supported.

Table 3.11: Three-stage least squares (3SLS) results

	Model 1		**Model 2**		**Model 3**	
	Eq (1) DV = CAP	Eq (2) DV = PERF	Eq (1) DV = CAP	Eq (2) DV = CHN_ROA	Eq (1) DV = CAP	Eq (2) DV = CHN_ROE
Independent Variables						
IMP_CUST	0.394 ***		0.317 ***		0.320 **	
	(0.001)		(0.010)		(0.017)	
FOBO	0.393 ***		0.499 ***		0.435 ***	
	(<0.001)		(<0.001)		(<0.001)	
CAP		0.777 ***		0.145 **		1.293
		(<0.001)		(0.053)		(0.251)
Control Variables						
RBU_TYPE		-0.382 ***		-0.184 ***		-1.540 *
		(0.009)		(0.006)		(0.087)
D_OFFER		0.075 *		0.015		0.271
		(0.076)		(0.413)		(0.275)
E_AGE		0.002		-0.001		-0.001
		(0.166)		(0.787)		(0.898)
D_AGE		-0.061		-0.156 ***		-1.086
		(0.614)		(0.006)		(0.170)
INVEST		0.028		0.083 *		1.647 **
		(0.788)		(0.093)		(0.021)

TECH_TUR		-0.011 (0.868)		-0.061 ** (0.046)		-0.294 (0.496)
MAR_TUR		0.027 (0.573)		0.029 (0.170)		0.429 (0.181)
Constant	1.114 *** (<0.001)	0.755 ns (0.154)	0.917 *** (<0.001)	-0.147 (0.523)	1.102 *** (0.001)	-4.678 (0.159)
R^2	0.2049	0.2003	0.2910	0.2057	0.2297	0.2036
F	29.75 ***	61.46 ***	37.38 ***	38.70 ***	26.86 ***	23.92 ***
N	109		91		90	

Note: Sample sizes are different due to the availability of secondary data. Estimates are shown in the table together with *p*-value in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 3.12: Indirect effects using bootstrapping with 90%, 95%, 99% bias-corrected CI

Model 1: Eq (1) DV = CAP, Eq (2) DV = PERF

Indirect Effect	Estimates	Boot SE	90% bias-corrected CI	95% bias-corrected CI	99% bias-corrected CI
IMP_CUST	0.306	0.137	(0.107, 0.569)	(0.073, 0.623)	(0.025, 0.741)
FOBO	0.302	0.086	(0.176, 0.453)	(0.148, 0.481)	(0.090, 0.529)

Model 2*: Eq (1) DV = CAP, Eq (2) DV = CHN_ROA

Indirect Effect	Estimates	Boot SE	90% bias-corrected CI	95% bias-corrected CI	99% bias-corrected CI
IMP_CUST	0.053	0.039	(0.005, 0.143)	(-0.001, 0.161)	(-0.018, 0.189)
FOBO	0.081	0.051	(0.013, 0.185)	(-0.001, 0.206)	(-0.031, 0.245)

Model 3*: Eq (1) DV = CAP, Eq (2) DV = CHN_ROE

Indirect Effect	Estimates	Boot SE	90% bias-corrected CI	95% bias-corrected CI	99% bias-corrected CI
IMP_CUST	0.481	0.545	(-0.100, 1.721)	(-0.228, 2.031)	(-0.529, 2.551)
FOBO	0.642	0.564	(-0.223, 1.632)	(-0.413, 1.820)	(-0.763, 2.211)

Note: Sample sizes are different due to the availability of secondary data. Model 1: N = 109; Model 2: N = 91; Model 3: N = 90; The bias-corrected CI is based on 5,000 bootstraps.

3.6 Theoretical Contributions, Managerial Implications, Limitations, and Future Studies

3.6.1 Theoretical contributions

This research makes two major theoretical contributions. One, this study defines a new construct, the *capability to digitize retail banking services*, to represent the ability of RBUs to continuously integrate and leverage emerging digital technologies to digitize retail banking services. We develop and validate a new measurement scale to measure this construct. This is a contribution because previous studies have discussed relevant capability but only conceptually without empirical measurement or examination. This study provides the first empirical evidence that captures the capability to digitize retail banking services and suggests that RBUs should continuously and actively explore opportunities to deploy and integrate emerging digital technologies to digitize service offerings to gain greater performance improvement. This construct is also consistent with the principles of the resource-based views and the resource-orchestration theory and extends it to the digitization context. Since this paper mainly focuses on the ability to use digital technologies to digitize existing retail banking services, future studies could further explore the capability to generate new digital retail banking services and examine its impacts on business performance improvement.

Two, this study proposes a new conceptual model to examine the drivers and outcomes of developing digitization capability. We tested the intermediate mechanism to explore and explain what the key drivers are that contribute to the capability to digitize retail banking services and subsequently contribute to business performance improvement. Firstly, we extend the capability-performance link to the context of the digitization of retail banking services. Our findings show that the capability to digitize retail banking services would positively affect business performance improvement. Second, we examine two drivers that are expected to contribute to digitization capability. Prior studies have noted the increasing digital demands and discussed the critical role of customers in digitization; however, the impact of focusing on digital-savvy customers has remained unexamined. Previous studies have discussed only the impact of front-office/back-office integration in the digitization of service offerings via case studies without empirical examination of its role in and impacts on digitization and/or business performance. Our findings show that the impacts of marketing strategy (focusing on digital-savvy customers) and internal efforts (aligning front-office back-office process) are critical drivers for RBUs to elevate their capability to digitize retail banking services. Furthermore, we also explain how these strategic and operational drivers influence the change in business performance indirectly through the capability to digitize retail banking services. The indirect effect of focusing on digital-savvy customers on business performance improvement is positive. It demonstrates the importance of segmenting customers based on their digital preferences and targeting digital-savvy customers. Additionally, this study considers only internal integration efforts, such as front-office back-office process alignment. Future research could explore the role and impacts of external integration, such as collaboration with FinTech firms. For instance, does FinTech collaboration enhance the digitization capability? Does FinTech collaboration contribute to greater growth in business performance? Does the length or extent of FinTech collaboration or characteristics (i.e., maturity, expertise) affect digitization capacity in RBUs?

3.6.2 Managerial implications

Our research findings offer RBUs various recommendations and caveats regarding efforts to digitize retail banking services.

First, although previous studies have shown the benefits of building digitization capability through case studies, the literature offers few practical guidelines to practitioners (e.g., bank managers) on how to build digitization capability. Managers of RBUs today face numerous challenges and changes in the digitization journey with limited resources with which to work. They should be aware that investing in emerging digital technologies is *not enough to gain competitive advantages*. RBUs need to continuously integrate their invested digital technologies to digitize their face-to-face retail banking services into those that can be offered digitally. Our findings show that RBUs with the ability to actively deploy, integrate, and leverage digital technologies, rather than merely holding or possessing the technologies, can build hard-to-imitate capabilities that result in positive impacts. The insights from this study also provide empirical support for previous case studies (e.g., Sia et al., 2016; D. Liu et al., 2011). We argue that RBUs may fail to reap the benefits of increasing their digital investments because they only purchase the technologies but cannot build such capability to use the technologies. This is extremely important for RBUs, especially for those that have not developed the awareness or those that have but are still hesitating to build the digitization capability to gain better performance. Being aware of the importance of digitization capability could help RBUs avoid unnecessary investments and stay competitive.

Second, the findings of a digital-savvy customer focus place greater emphasis on RBUs' strategic decisions in their digitization of retail banking services. Some RBUs may start or continue the digitization journey without clear guidelines. The traditional route of segmenting customers according to customer demographics may no longer be sufficient for RBUs to successfully find and target the right customers in the digital age. RBUs should be well advised about the difference between traditionalists and digital-savvy customers. More importantly, RBUs should be aware of and able to seize the value of their digital-savvy customers. It is necessary for managers to segment and distinguish customers based on their digital preferences and banking behaviors. By doing so, RBUs can allocate their resources to their digital users, and make relevant decisions and actions on these customers. The findings show that focusing on digital-savvy customers is critical for the development of digitization capability. We also show that such a strategic decision is also critical to improving business performance through digitization capability. RBUs should consider this as a central strategic consideration. RBUs can benefit from focusing on digital-savvy customers to enhance their digitization capability and gain better performance from offering digital retail banking services.

Third, other than strategic decisions, internal efforts (i.e., front-office back-office process alignment) should also be treated as key drivers for RBUs in their digitization of retail banking services. For managers, aligning the front-office back-office process may not be a focal mission in the digitization journey. However, this study shows that *synchronizing* their customer-facing front-end and operations back-end acts is a key driver for developing digitization capability. The alignment is helpful for managers to identify what features are most desired by customers, which digital technologies are useful in enhancing the customer experience and customer-bank interactions, which issues require immediate attention, and which type of information must be collected and shared. An aligned front-office back-office process enables RBUs to make better decisions in their decision-making process. Though we did not find evidence that aligning front-office back-office process leads to a stronger impact than marketing strategy on business performance improvement, aligning front-office and back-office processes can help RBUs develop digitization capability.

3.6.3 Limitations and future studies

Though this study makes several theoretical and managerial contributions, it has some limitations.

First, our study relies mainly on the subjective responses from a single informant. Previous studies have suggested using multiple informants to increase the reliability and validity of survey studies (Fynes & De Búrca, 2005; Rosenzweig & Roth, 2004). However, using multiple informants would largely complicate the survey design and collection process. We believe that the single response did not limit the information needed for this study since we located the best person who knows the digitization information very well in the RBUs and at the same time, leveraged well-established multi-item constructs for our variables. Additionally, to alleviate the potential issue that all data are collected from a single source, we have implemented the suggested techniques and procedures used by Podsakoff et al. (2003) to control the potential common method bias. Particularly, we have also collected secondary data and used objective financial data (i.e., change of ROA, change of ROE) as the business-level performance measure to further alleviate the potential problems due to common method bias (de Koster et al., 2011; Menor & Roth, 2008; Rosenzweig & Roth, 2004).

Second, our sample size (N = 109) is small. Even though the response rate is high, with an 80% response rate (N = 32) from a total of 40 retail banks and a 40% response rate (N = 124) from a total of 230 credit unions, the overall sample size is still small. The sample size prevented us from conducting a full SEM in which both the measurement model and structural model can be examined together. However, since this study focused on the Canadian retail banking industry, the total sampling frame itself is quite limited with only 40 retail banks and 230 credit unions. However, it is unlikely for a larger sample size could invalidate our findings given the robust results we obtained in this study. Future studies can examine and extend our findings in a larger sample and particularly in another environment.

3.7 Conclusion

This study developed a theoretical model to explore the drivers and outcomes of digitization capability. We designed a survey to collect primary data from RBUs in Canada to empirically test the model. Our findings show that the marketing-level strategic decisions (focusing on digital-savvy customers) and operational efforts (aligning front-office back-office process) are key drivers of digitization capability. We also show that elevating the capability to digitize retail banking services can lead to positive changes in business performance. Furthermore, digitization capability acts as a mediator to explain how strategic and operational efforts are transformed into improved performance. This study contributes to emerging digitization literature by illustrating that developing the capability of leveraging digital technologies in the digitization of service offerings could help RBUs to gain better improvement in their business performance. It contributes to and extends the resource-based view and resource orchestration theory to the digitization context. Additionally, this study provides insights into the capability-performance relationship in the context of the digitization of retail banking services.

Chapter 4
Conclusions

4.1 Overall Conclusions

This dissertation focuses on the digitization of financial services in financial institutions (FIs) and investigates the impacts of digitization efforts on firm performance. Digitization of financial services is pervasive and continuously trending in FIs. If executed properly, it is expected to help FIs remain competitive and continue to grow. Digitization of financial services is about employing digital technologies to improve firm performance. Essentially, digital technologies act as the supporting backbone. However, despite years of investment and the implementation of digital technologies, FIs are still wasting money on digital technologies and suffering a high failure rate when applying digital technologies. FIs are making huge investments in digital technologies but investors are losing confidence to see the expected returns the invested digital technologies can bring. FIs are possessing more digital technologies but many lack the capability to fully leverage the technologies to digitize their service offerings. As such, this dissertation explores a key problem: *whether* and *how* FIs can utilize invested emerging digital technologies to achieve improved performance? In Chapter 2, we introduce a new approach to help FIs evaluate their return on investment in digital technologies. In Chapter 3, we test a model to link the capability of utilizing digital technologies to digitize service offerings to performance improvement. We show that the digitization of financial services is not solely about digital technology itself. FIs that can successfully track digital investment, deploy resources, and develop digitization capability could reap the benefits. Furthermore, in both studies, we also consider and examine the other internal (e.g., internal process alignment) and external efforts (e.g., collaboration with FinTech firms) FIs have made in the digitization of financial services.

Study 1. ***Does financial institutions' investment in emerging digital technologies pay back?*** The answer is No. In Chapter 2, we introduced a new evaluation approach to help FIs assess the return of investment on digital technologies and explain why FIs have failed to reap the rewards. Since there is no tool to help FIs track their performance from investing in digital technologies, we proposed a new method using data envelopment analysis (DEA) to evaluate the return on digital investment with the consideration of allocating shared technological resources internally. We adopted a two-stage analysis approach, in which we first evaluated the efficiency score that represents the return on digital investment, and then conducted a bootstrapped truncated regression to examine selected explanatory factors. We showed that, despite increasing technological progress, FIs were still experiencing decreasing returns of digital investment over time. Our findings also show that to gain higher returns, FIs should pay close attention to their internal efforts such as enhancing their innovation capability as well as their external efforts such as collaborating with FinTech firms.

This study provides several theoretical contributions. First, we extend the DEA literature by introducing a new approach to evaluate the return on digital investment of heterogeneous FIs in the digital age. Studies using DEA techniques have mainly focused on bank-level or bank-branch level performance with labor as the major cost consideration, and as a result, have overlooked the lack of homogeneity concerns among FIs and also have lacked thorough investigation of technology-related expenditures. We develop a new resource-allocation DEA model that (a) identifies the non-homogeneity nature of FIs based on their income structures, (b) evaluates the aggregate efficiency scores that can be used to benchmark FIs with their true peers, and (c) enables shared technological resources to be optimally re-allocated within FIs. Second, we contribute to the banking performance literature by examining how internal effort (i.e., innovation capability) and external effort (i.e., collaboration with FinTech firms) help improve FI performance in the digital age. Specifically, utilizing the technology management literature, we show that innovation capability is important in improving performance. We complement the broader BSR literature on the context of digitization of financial services by providing empirical support for the association between the bank–FinTech partnership and performance. Chiefly, we show that a moderation effect exists in FinTech collaboration whereby larger FIs are more likely to gain better performance from collaborating with FinTech firms, but smaller ones are better off when playing alone.

More importantly, this study offers managerial insights for practitioners, including FI executives, investors, and policymakers, with respect to their efforts in investing and managing digital technologies. We show that simply investing in digital technologies is not enough to achieve better performance. This failure to reap the rewards highlights the long-overlooked issue of FIs' inefficient resource management. While FIs have been pouring millions of dollars into digital technologies, we should recognize that the volume of investment in digital technologies does not guarantee the desired return. What holds FIs back is their inability to accommodate their operations along their digitization journey. The effectiveness of the technological resource depends on how well FIs are deploying and using them internally, e.g., optimally allocate digital technologies into the sub-sections within FI and improve efficiencies across all sub-sections. Learning more about the internal operations of FIs, especially efficient management of technological resources, should also be a critical task for FIs in the digitization journey.

Study 2. ***Does financial institutions' capability to digitize financial services improve their business performance?***

The answer is Yes. In Chapter 3, we focus on the digitization of service offerings in FIs and tested a theoretical model to explain how elevating digitization capability— the ability to utilize emerging digital technologies to digitize service offerings—can contribute to better business performance. We propose a new theoretical model in which the drivers and outcomes of the digitization capability are linked together. We collect both primary and secondary data from retail banks and credit unions in Canada to empirically examine the model. We showed that elevating the ability to utilize emerging digital technologies to digitize service offerings is positively associated with performance improvement. We also show that focusing on digital-savvy customers and aligning front-office back-office process are two important drivers for FIs in developing their digitization capability; these efforts also indirectly contribute to performance improvement.

This study offers two primary theoretical contributions. First, given the existing literature's inadequate exploration of digitization capability, we define a new construct, *capability to digitize retail banking services*, to capture the ability of FIs to continuously integrate emerging digital technologies so as to digitize existing face-to-face retail banking services into the ones to be offered digitally. We developed and validated the new measurement scale to measure this construct. Particularly, we extended the principles of the resource-based views and resource-orchestration theory to the digitization of financial services context. Since digital technologies can be purchased from external sources, the technology itself provides limited value for FIs. We show that, rather than holding or possessing digital technologies, it is the *development of the difficult-to-imitate capability* that enables FIs to gain competitive advantages and superior performance in this highly competitive digital age. Second, we propose and empirically test a new model that links the drivers and the outcomes of digitization capability. Previous studies have shown insufficient empirical evidence on the relationship between a FI's digitization capability and performance improvement. The research on the key drivers for digitization capability is also limited. We extend the capability-performance link to the context of the digitization of financial services and showed that elevating digitization capability is positively associated with improvement in business performance that FIs can obtain from offering digital retail banking services. We also utilize and extend the marketing and process integration literature to the digitization context. By examining the intermediate mechanisms in the capability drivers-capability-capability outcomes, we show that marketing strategic decisions (i.e., focusing on digital-savvy customers) and operational efforts (i.e., aligning front-office back-office process) are acting as key drivers that motivate the development of digitization capability and indirectly contributing to business performance improvement.

This study also offers practical insights for FIs regarding their efforts in the digitization of service offerings. First of all, we showed that, in line with Study 1, investing in and possessing technologies alone is not enough for FIs to maintain competitiveness and gain superior performance in the digital age. FIs can buy any digital technology they need, but it is the development of the hard-to-imitate ability to actively deploy, integrate, and leverage emerging digital technologies to digitize existing face-to-face services into those that can be offered digitally that helps to gain better performance. Second, we demonstrate that focusing on digital-savvy customers is the right strategic decision for FIs in the digitization of financial services. Given the increasing digital demands and changing customer behaviors, the traditional way of segmentation based on demographics is insufficient for FIs to successfully focus efforts on the right customers in the digital age. FI managers should be aware of and be able to seize the value of their digital-savvy customers. Focusing on digital-savvy customers is critical in elevating digitization capability and also enhance performance. Third, we show that aligning the front-office back-office process is also an important operational effort for FIs aiming to develop digitization capability and improve performance. Similar to Study 1 whereas resource management is often overlooked by FIs, synchronization between front-office and back-office is the operational effort that has also been seriously neglected in FIs' digitization journey. Internal alignment is important for FIs to identify what features customers most desire, which digital technologies are most useful in enhancing customer experiences, which issues require immediate attention, and what information must be collected and shared in a timely fashion.

4.2 Future Research

This dissertation also provides several directions for future research. Future studies can investigate topics related to FinTech collaboration and the capability to generate new retail banking services.

4.2.1 FinTech collaboration

In Chapter 2, we examined the impact of collaborating with FinTech firms on improving the return of digital investment. FinTech collaboration in our study is considered as a binary state: presence or absence. However, the impact of FinTech collaboration on the digitization of financial services and firm performance may be affected by other FinTech firm-related characteristics, which are missing in this dissertation. We suggest future studies explore: *How do FinTech collaborations and their characteristics affect the digitization of financial services and firm performance?*

For instance, would FinTech collaboration, as external drivers, influence the digitization capability of FIs and performance? And particularly, would (i) the type of FinTech firms (e.g., established vs. start-up); (ii) the stage (i.e., early vs. late) of collaborating with FinTech firms; (iii) the extent or length of collaboration; and (d) the performance of FinTech firms, make a difference?

4.2.2 Capability to develop new retail banking services

In Chapter 3, we focused on the digitization capability of FIs to integrate emerging digital technologies to transform existing face-to-face retail banking services to be offered digitally and examine its impact on performance improvement. However, looking forward, it may not be enough to focus merely on the digitization of existing banking services. Rather, introducing *novel* digital banking services is also important for FIs (Holmlund et al., 2017). The advancement of digital technologies is enabling the entire financial services industry to digitize existing services offerings and to develop entirely novel digital services (Gomber et al., 2017). As such, we propose that future research can explore: *Does the capability to generate entirely new digital services improve firm performance*? Additionally, future research can also examine the moderators that can impact the effect of the capability to generate new digital retail banking services on performance improvement. For instance, would large FIs benefit more than small FIs from the capability to digitize existing or new retail banking services? Would the relationship between digitization capability and firm performance differ under environmental uncertainties?

For instance, would FIs benefit more from building the capability to digitize existing/new retail banking services when the market/technological uncertainty is high?

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Appendices

Appendix 1 Supplementary Materials for Chapter 2

Appendix 1.1

Table A1.1: A review of data envelopment analysis studies in the banking industry

Authors	Level of analysis	Sample	Method	Inputs	Outputs
Cook, Hababou, and Tuenter (2000)	Branch-level	20	DEA	Number of service staff, number of sales staffs, number of support staff, number of other staff	Number of counter level deposits, number of transfers between accounts, number of retirement savings plan openings, number of mortgage accounts opened
Cook and Hababou (2001)	Branch-level	20	DEA	Total number of full-time equivalent service staff, total number of full-time equivalent sales staff, total number of full-time equivalent support staff and other staff as shared inputs	Total number of menu account transactions, number of Visa cash advances, number of commercial deposit transactions, number of RSP account openings, number of mortgages transacted, number of variable rate consumer loans transacted
Bala and Cook (2003)	Branch-level	180	DEA	Number of full-time employees, total accounts opened, number of deposits and transfers, number of withdrawals and updates	Number of retirement savings plans sold, total of all loans and mortgages
Cook, Seiford, and Zhu (2004)	Branch-level	1200	DEA	Full time equivalent counts staff, including sales, services, support and other staff, operating expenses	Service transactions, sales transactions
Paradi and Schaffnit (2004)	Branch-level	90	DEA	Staff, IT expense, rent, other non-interest expenses	Deposits, loans, fee income, deposit spread, loan spread
Camanho and Dyson (2005)	Branch-level	144	DEA	Number of branch and account managers, number of administrative and commercial staff, number of tellers,	Number of general service transactions

				operational costs	
Cook and Zhu (2005)	Branch-level	100	DEA	Staff (sales; service; other)	Service outputs; sales outputs
Yang, Wong, Xu, Liu, and Steuer (2010)	Branch-level	14	DEA	Business reviews, contacts, registrations, KPI, future value added	Customer service, commercial income
Tortosa-Ausina, Grifell-Tatjé (Armero, and Conesa, 2008)	Bank-level	50	DEA (Malmquist) + bootstrapped	Labor (total labor expenses), capital (physical capital), purchased funds	Loans, core deposits, non-interest income
García-Cestona and Surroca (2008)	Bank-level	50	DEA + ANOVA	Employees expenditure, operating expense, depreciation expenses	Average balance of deposits, Herfindahl index, profits after taxes, interest rates for overdrafts, Charitable-social programs, loans to public administration
Sahoo and Tone (2009)	Bank-level	78	DEA	Fixed assets, borrowed funds, labor	Investment, performing loan assets, non-interest income
Ray and Das (2010)	Bank-level	71	DEA	Funds, labor, capital, quasi-fixed inputs	Investment, earning advances, other income
Wanke, Barros, and Emrouznejad (2016)	Bank-level	13	FDEA + Bootstrapped truncated regression	Total cost, employee cost	Total deposits, income before tax
Matousek and Tzeremes (2016)	Bank-level	37	Conditional DEA	Property, plant and equipment as bank capital, deposits, number of employees	Securities and loans
Kevork, Pange, Tzeremes, and Tzeremes (2017)	Bank-level	644	Malmquist Index + probabilistic approach	Total assets, total employees, total deposits	Net loans, securities investment
Du, Worthington, and Zelenyuk (2018)	Bank-level	140	DEA + bootstrapped truncated regression	Total interest expenses, and non-interest expense (personal expense, other operating expenses)	Aggregated income combined net interest income, net fees and commissions and other operating income
Boussemart, Leleu, Shen, Vardanyan, and Zhu (2019)	Bank-level	30	DEA	Interest expenses, non-interest expenses	Total loans, interest income, non-interest income, non-performing loans

Appendix 1.2

The components summary for each income stream, adapted from Copeland (2012).

(1) Traditional income category includes:

- a. interest and fee income on loans;
- b. income from lease financing receivables;
- c. interest income on balances due from depository institutions;
- d. interest and dividend income on securities (except for mortgage-backed securities);
- e. interest income on federal funds sold and securities purchased under agreements to resell;
- f. other interest income;
- g. income from fiduciary activities;
- h. service charges on deposit accounts in domestic offices;
- i. net gains (losses) on sales of loans and leases;
- j. net gains (losses) on sales of other real estate owned;
- k. net gains (losses) on sales of other assets (excluding securities);
- l. realized gains (losses) on held-to-maturity securities;
- m. realized gains (losses) on available-for-sale securities;
- n. interest expenses (excluding the amounts assigned to securitization and non-traditional income categories).

(2) Securitization income category includes:

- a. net servicing fees;
- b. net securitization income;
- c. interest and dividend income on mortgage-backed securities minus associated interest expense.

(3) Non-traditional income category includes:

- a. trading revenue;
- b. investment banking, advisory, brokerage, and underwriting fees and commissions;
- c. venture capital revenue;
- d. insurance commissions and fees;
- e. interest income from trading assets minus associates interest expense.

Appendix 1.3

Summary of the thematic analysis coding.

To extract qualitative information and integrate them into a structured data format. We apply the triangulation strategy. The steps are summarized as follows:

(1) Qualitative data collection. The primary data is annual reports extracted from SEC.GOV. According to the filing policy, BHCs need to disclose the company's results, events or information, merger or acquisition in their 10-K filing. Therefore, we downloaded all the 10-K filings from 2010 to 2016 for the 81 BHCs and used these for the thematic analysis. Archival data, like annual reports, may be associated with less bias because more objective data were collected;

(2) Identify and code relevant concepts or categories. Several key concepts are explored to check BHC's disclosure of "*relationship*" with technology firms. More especially, we search the description relates to "*operation management*", "*operating risk*", "*information system*" and "*business infrastructure*". Due to the limited disclosure BHCs made in their annual report, we limit the relevant concepts that are relevant to work with "*third-party*" firms. For example, we code BHCs are "*rely on the third-party*" if they indicate they "*heavily rely on the third-party who has the ability to deliver technology that is of higher quality, lower cost, or both*", or "*rely on communications, information, operating control systems technology from third-party service providers*"; we code BHCs are "*work with the third-party*" if they, for instance, state that they "*outsource certain functions, such as customer-facing websites, and developing software for new products and services*".

(3) Thematic analysis. As the analysis gradually developed, certain categories are collapsed and combined into a major theme, as "*Partnership with technology firms*".

(4) Binarization of thematic data. As indicated in Fakis et al (2013), the approaches for transforming qualitative themes into quantitative data are different in various studies. Here, a new variable- "*partnership*" is generated and binarized by assigning 1 when the theme is identified for certain BHC and 0 otherwise. This binary variable "*partnership with technology firms*" is then used in the second stage analysis.

Appendix 1.4

Linear Formulation.

An equivalent linear formulation is provided below to convert this nonlinear model to a linear setting. The objective function e_{agg} is now defined as

$$e_o = \max \left[\sum_{R_K \in L_{N_{p0}}} \sum_{r \in R_K} (\mu_r y_{rj_0} + \mu_k^0) / \sum_{i \in I_K} \vartheta_i \, x_{ij_0} \right] \quad \text{Eq. (A1.4.1)}$$

with the changes of variables $z_{iR_kP} = v_i \, \alpha_{iR_kP}$, and note that (Cook et al., 2013)

$$\sum_{R_K \in L_{N_p}} \alpha_{iR_K N_p} = 1 \rightarrow v_i \sum_{R_K \in L_{N_p}} \alpha_{iR_K N_p} = v_i \rightarrow \sum_{R_K \in L_{N_p}} z_{iR_K N_p} = v_i$$

By applying the Charnes, Cooper, and Rhodes (1978) usual transformation $t = 1/\sum_i v_i x_{ij_0}$, and defining $\mu_r = tu_r$, $v_i = t\vartheta_i$, $\gamma_{iR_K N_p}$=t$z_{iR_K N_p}$, the model now turns to

$$e_o = \max \sum_{R_K \in L_{N_{p0}}} \sum_{r \in R_K} (\mu_r y_{rj_0} + \mu_k^0) \quad \text{Eq. (A1.4.2)}$$

subject to

$\sum_{R_K \in L_{N_{p0}}} \left(\sum_i \gamma_{iR_K N_p} x_{ij_0} \right) = 1$ Eq. (A1.4.3)

$\sum_{r \in R_K} \mu_r y_{rj} - \sum_{i \in I_K} \gamma_{iR_k p} x_{ij} + u_k^0 \leq 0 \; \forall j \in N_P, R_K \in L_{N_P}, p = 1, \ldots, P$ Eq. (A1.4.4)

$\sum_{R_K \in L_{N_p}} \gamma_{iR_K N_p} = \vartheta_i \; \forall i, p = 1, \ldots, P$ Eq. (A1.4.5)

$\vartheta_i a_{iR_K N_p} \leq \gamma_{iR_K N_p} \leq \vartheta_i b_{iR_K N_p} \; \forall i, p = 1, \ldots, P$ Eq. (A1.4.6)

$\mu_r, \vartheta_i, \gamma_{iR_K N_p} \geq \varepsilon \; \forall i, R_K, p = 1, \ldots, P$ Eq. (A1.4.7)

Appendix 1.5

Discussion on separability tests and results.

It is important to test if the separability condition holds or not. This "separability" concern has been discussed in Simar and Wilson (2011). Daraio, Simar, and Wilson (2018) provided the tests and demonstrated empirical examples.

As explained in Daraio et al. (2018), the environmental factors would impact the shape of the production set, the attainable set of values, and the distribution of inefficiencies inside. Whether the efficiency scores can be used to benchmarking performances while facing the environmental variables would depend on if this separability condition (L. L. Simar & Wilson, 2007) holds or not. The separability condition is stated in Assumption 2.1.

- If the separability condition holds, studies can move forward to conduct the second stage analysis; however, it may suggest that explanatory variables influence only the inefficiencies or the distance from frontier, but not the shape nor the level of the boundary of the attainable set.
- If the separability condition is violated, using the two-stage approach of Simar and Wilson (2007) may result in misleading results; and hence, a general way, as suggested by Daraio et al. (2018), is the probabilistic approach. This approach can be found in studies, such as Bădin, Daraio, and Simar (2010, 2012, 2014, 2019).

As such, testing the separability condition is critical for us to move to the second-stage analysis. We followed the instructions, suggested in Daraio et al. (2018), to test the separability. The step-by-step process is discussed and presented as follows.

Our data include 3 outputs and 2 inputs. There are 6 explanatory variables. 3 are continuous, and 3 are categorical. As explained in Daraio et al. (2018), the goal is to test the Assumption 2.1. To do this, one can compare the expected value of unconditional efficiency scores and the expected value of the conditional efficiency scores to see if the difference is significantly different.

Step 1: Considering the "*curse of dimensionality*", we first followed the suggestion in Daraio et al. (2018) and aggregated the two inputs into a single measure, *average cost*, which is the average of labor cost and technology cost; and aggregated three outputs into a single measure, *average income*, which is the average of the three incomes. In this way, the dimensionality is reduced from 5 to 2.

Step 2: Due to the small sample size we have, subsetting a smaller subsample would later result in a much smaller size in the split groups; therefore, we decided to use the entire sample (N=81). For each year, we randomly split each sample into two groups, as equally as possible.

Group 0: $n_0 = 40$, which will be used to compute the unconditional efficiency.

Group 1: $n_1=41$, which will be used to compute the conditional efficiency.

Step 3: We simply test separability by considering only one explanatory variable (r=1) each time.

Step 3.1: We included the continuous explanatory variable, *Innovation capability*.

Step 3.2: Using Daraio et al. (2018) equations (5.1) to (5.6), we first computed the conditional and unconditional efficiency scores from naïve models, and then we computed the bias-corrected scores.

Step 3.3: The basic idea is to examine if the means of conditional efficiency and unconditional efficiency differ or not. We set the null hypothesis as "*the mean difference is zero",* and the alternative as "*the mean difference is not zero*". The null hypothesis shares the same idea with Assumption 2.1, therefore, a testing result of non-rejection would suggest that the means of conditional efficiency and unconditional efficiency don't differ, and hence, can be considered as a support of Assumption 2.1. Considering such, we tested the means difference between group n_0 and group n_1 by conducting a t-test. The equal variances test was also conducted before the t-test.

Step 3.4: The results were summarized in Table A1.1. We presented group means and p-value separately for each year from the year 2010 to 2016, and separately for the naïve model, bootstrap with 1000 replications, and bootstrap with 2000 replications.

Step 4: We then repeat Steps 3.1 to 3.4 for the other continuous explanatory variables (control variables). The results were displayed in Table A1.2.

Step 5: For the categorical explanatory variables, we have *peer group, partnership,* and *diversification*. Peer group has three levels; partnership and diversification have two levels. Since our sample is small, testing the categorical explanatory variables with more than two levels means we have to split our sample into, at least, four subsamples (n_0 and n_1 with three subgroups), and all with very unequal sizes. It was also challenging to test for partnership and diversification. For instance, the 2010 data shows that there were 15 BHCs had partnerships with technology firms. The splitting would result in very unequal subsamples, for instance, n_0=40, n_1 (*with partnership*) = 3, n_1 (*no partnership*) =38. The benchmarking results, therefore, were not reasonable. Thus, considering the complexity to conduct the test and explain the results, we only tested the separability conditions for our continuous explanatory variables. We expect future studies can extend it to further test the categorical explanatory variables.

Table A1.2: Separability tests results

	Naïve				B1=1000 Bootstrap replications				B2=2000 Bootstrap replications			
Innovation Capability	n_0_mean	n_1_mean	p_value	B-H adjustment	n_0_mean	n_1_mean	p_value	B-H adjustment	n_0_mean	n_1_mean	p_value	B-H adjustment
2010	0.6722	0.6069	0.1170	0.6151	0.4785	0.4730	0.8511	0.8511	0.4773	0.4700	0.8077	0.8481
2011	0.6055	0.6307	0.5768	0.8162	0.4535	0.4141	0.2636	0.6151	0.4577	0.4136	0.1831	0.6151
2012	0.6151	0.6292	0.7507	0.8297	0.4655	0.4253	0.2087	0.6151	0.4652	0.4263	0.2301	0.6151
2013	0.5905	0.6259	0.4271	0.7474	0.4562	0.4725	0.6079	0.8162	0.4535	0.4722	0.5653	0.8162
2014	0.6500	0.6355	0.7353	0.8297	0.4940	0.5246	0.3495	0.7062	0.4939	0.5232	0.3699	0.7062
2015	0.6595	0.6803	0.6219	0.8162	0.5000	0.5426	0.2224	0.6151	0.5029	0.5409	0.2586	0.6151
2016	0.6651	0.6493	0.6993	0.8297	0.4717	0.5319	0.0464	0.5397	0.4729	0.5311	0.0514	0.5397
NPL	n_0_mean	n_1_mean	p_value	B-H adjustment	n_0_mean	n_1_mean	p_value	B-H adjustment	n_0_mean	n_1_mean	p_value	B-H adjustment
2010	0.6451	0.6373	0.8553	0.8873	0.4635	0.5161	0.0901	0.2703	0.4655	0.5140	0.1333	0.3429
2011	0.6266	0.6332	0.8873	0.8873	0.4423	0.4117	0.3604	0.5046	0.4428	0.4115	0.3526	0.5046
2012	0.6035	0.6155	0.7762	0.8579	0.4197	0.4611	0.1796	0.3429	0.4218	0.4626	0.1774	0.3429
2013	0.6554	0.5910	0.1607	0.3429	0.4562	0.4426	0.6591	0.7690	0.4567	0.4407	0.6077	0.7690
2014	0.6288	0.6756	0.2636	0.4613	0.4737	0.5366	0.0448	0.2352	0.4725	0.5369	0.0425	0.2352
2015	0.6347	0.6779	0.3088	0.4988	0.4886	0.5437	0.0881	0.2703	0.4843	0.5439	0.0708	0.2703
2016	0.6580	0.6394	0.6551	0.7690	0.5335	0.4626	0.0174	0.2352	0.5327	0.4634	0.0227	0.2352
Capital Adequacy	n_0_mean	n_1_mean	p_value	B-H adjustment	n_0_mean	n_1_mean	p_value	B-H adjustment	n_0_mean	n_1_mean	p_value	B-H adjustment
2010	0.6608	0.6521	0.8301	0.9632	0.5170	0.5187	0.9632	0.9632	0.5239	0.5203	0.9111	0.9632
2011	0.6036	0.6347	0.4988	0.7832	0.4784	0.5011	0.5221	0.7832	0.4774	0.5004	0.5215	0.7832
2012	0.6229	0.6206	0.9583	0.9632	0.4841	0.4941	0.7590	0.9632	0.4857	0.4959	0.7537	0.9632
2013	0.6577	0.5774	0.0684	0.2032	0.4976	0.4342	0.0427	0.1848	0.4987	0.4364	0.0427	0.1848
2014	0.6456	0.6865	0.3685	0.7035	0.4557	0.5262	0.0408	0.1848	0.4597	0.5272	0.0466	0.1848
2015	0.6892	0.6866	0.9506	0.9632	0.5777	0.5170	0.0528	0.1848	0.5778	0.5155	0.0486	0.1848
2016	0.6431	0.7145	0.0774	0.2032	0.5486	0.5944	0.1851	0.3887	0.5491	0.5941	0.1821	0.3887

Notes: The Benjamini-Hochberg (B-H) adjustment (Benjamini & Hochberg, 1995) is conducted to control the false discovery rate in multiple comparisons.

So far, as shown in Table A1.2, in all cases, we cannot reject the null hypothesis (Assumption 2.1) with p-values greater than 0.01, and in most cases, the p-values are more than 0.1, the results, therefore, suggesting that the Assumption 2.1 is not violated and the separability condition holds. Furthermore, because we conduct 21 mean comparison tests for each continuous explanatory variable, the probability of committing false positive may increase when conducting multiple comparisons. A p-value less than 0.05 may happen purely by chance and thus, require proper adjustment. The Benjamini-Hochberg adjustment ("B-H", Benjamini & Hochberg, 1995) is used as post-hoc analysis. The B-H adjustment is a powerful and robust method to control the false discovery rate (i.e., the expected proportion of rejected null hypotheses that are incorrect rejections) in multiple comparisons (Benjamini, 2010; Benjamini & Yekutieli, 2001; Jafari & Ansari-Pour, 2019). We conduct the B-H adjustment for each explanatory variable and present the adjusted p-values together with raw p-values in Table A1.2. The results show that no value remains significant. As a result, we conclude that, in all cases, there is no violation of the separability condition, allowing us to move forward to conduct the second stage analysis using the Simar and Wilson's (2007) two-stage approach.

Back to our study, we would like to discuss the theoretical and practical impacts when the separability condition holds. Daraio et al. (2018) pointed out that if the separability condition holds then the explanatory variables used in the second-stage analysis could only affect the distributions of inefficiencies (in our case) but not the shape of the frontier. In this way, the next question is: *is this a realistic assumption in our case? What is the impact on our second-stage analysis?*

In our study, we conducted a novel resource-allocation model for nonhomogeneous DMUs with shared-inputs. An aggregate efficiency score was obtained by using the three-step approach (Cook, Harrison, Imanirad, Rouse, & Zhu, 2013; Cook, Harrison, Rouse, & Zhu, 2012). This externally obtained efficiency score was then used as the dependent variable in the second-stage analysis by applying algorithm 1 in Simar and Wilson (2007). This aggregate efficiency score can be considered as the weighted average of three subunits' efficiencies. That means, for a BHC to get its aggregate efficiency equals to 1, it has to be efficient (subunit's score equals to 1) in all three subunits. As we have shown in the study, not all BHCs were efficient in all three subunits (i.e., the income streams); some are efficient in traditional banking activities while others are efficient in new financial services. When we derive the aggregate efficiency scores, only ten data points (the aggregate efficiency scores) showed the efficiency scores equal to 1, and these BHCs were excluded in the second stage analysis since they were considered as the "*frontier*" of aggregate efficiency. By conducting the outlier diagnostics and the Kernel estimated densities (Du, Worthington, & Zelenyuk, 2018) with and without these ten "*efficient-in-all*" BHCs, we found that only the Kernel distribution tail was longer but the distribution of scores remained similar. In this case, we argued that, when the separability condition holds, the explanatory variables affect the distribution of inefficiencies and could also potentially impact the shapes of subunits' frontiers. Our empirical results were, thus, reliable and consistent with the support of several robustness tests. Practically, since the aggregate efficiency scores were derived from three income-generating activities (i.e., the subunits), our results suggest that BHCs can still gain improvements on those inefficient income streams and get a better performance overall.

Finally, we acknowledged that different methods have been developed to allow researchers to employ statistical tools to carry out a second-stage analysis. For example, early studies applied Tobit regression in a second-stage analysis, Simar and Wilson (2007) developed the two-stage bootstrapped truncated regression approach, Banker and Natarajan (2008) justified and adopted the DEA+OLS approach, Bădin, Daraio, and Simar (2010, 2012, 2014) proposed the conditional DEA method, etc. However, different paradigms exist and no agreement had been achieved. Different approaches are criticized due to their own assumptions. As Banker, Natarajan, and Zhang (2019, P383) argued "*any model is by necessity a simple abstraction of reality, and thus the maintained assumptions are rarely true in their entirety in practice. The key question is to what extent the assumptions deviate from reality and reasonable expectations based on prior research*". We hope that future studies can examine and extend our study by employing other methods.

Appendix 1.6

BHC resource allocation, and weights across subunits, results of 2010 as an example.

Table A1.3: $\boldsymbol{\alpha_{iR_kp}}$ values for resource-allocation model (year = 2010)

BHC	α_{1R_1p}	α_{1R_2p}	α_{1R_3p}	α_{2R_1p}	α_{2R_2p}	α_{2R_3p}
ACNB	0.10	0.23	0.67	0.13	0.10	0.77
AMNB	0.80	0.10	0.10	0.80	0.10	0.10
AROW	0.73	0.17	0.10	0.66	0.24	0.10
ASB	0.10	0.80	0.10	0.80	0.10	0.10
BAC	0.10	0.10	0.80	0.10	0.10	0.80
BANF	0.80	0.10	0.10	0.80	0.10	0.10

BANR	0.80	0.10	0.10	0.80	0.10	0.10
BBT	0.14	0.10	0.76	0.10	0.10	0.80
BMTC	0.80	0.10	0.10	0.80	0.10	0.10
BOH	0.10	0.80	0.10	0.10	0.80	0.10
BOKF	0.10	0.80	0.10	0.10	0.80	0.10
BPOP	0.80	0.10	0.10	0.80	0.10	0.10
BXS	0.19	0.10	0.71	0.10	0.10	0.80
C	0.10	0.10	0.80	0.10	0.10	0.80
CBSH	0.10	0.80	0.10	0.33	0.33	0.33
CBU	0.80	0.10	0.10	0.80	0.10	0.10
CCNE	0.80	0.10	0.10	0.33	0.33	0.33
CHFC	0.80	0.10	0.10	0.80	0.10	0.10
CMA	0.80	0.10	0.10	0.80	0.10	0.10
COF	0.80	0.10	0.10	0.80	0.10	0.10
COFS	0.10	0.10	0.80	0.10	0.10	0.80
COLB	0.80	0.10	0.10	0.80	0.10	0.10
CSFL	0.10	0.80	0.10	0.13	0.77	0.10
CTBI	0.80	0.10	0.10	0.80	0.10	0.10
CZNC	0.80	0.10	0.10	0.75	0.15	0.10
DFS	0.80	0.10	0.10	0.80	0.10	0.10
EFSC	0.80	0.10	0.10	0.80	0.10	0.10
EWBC	0.80	0.10	0.10	0.80	0.10	0.10
FCF	0.80	0.10	0.10	0.80	0.10	0.10
FCNCA	0.80	0.10	0.10	0.80	0.10	0.10
FFKT	0.10	0.80	0.10	0.33	0.33	0.33
FHN	0.10	0.10	0.80	0.10	0.10	0.80
FIBK	0.10	0.80	0.10	0.80	0.10	0.10
FISI	0.38	0.52	0.10	0.41	0.49	0.10
FITB	0.80	0.10	0.10	0.80	0.10	0.10
FMNB	0.80	0.10	0.10	0.80	0.10	0.10
FULT	0.80	0.10	0.10	0.80	0.10	0.10
GABC	0.10	0.80	0.10	0.80	0.10	0.10
HBAN	0.80	0.10	0.10	0.80	0.10	0.10
HOMB	0.80	0.10	0.10	0.80	0.10	0.10
INDB	0.80	0.10	0.10	0.80	0.10	0.10
KEY	0.10	0.80	0.10	0.10	0.80	0.10
KTYB	0.80	0.10	0.10	0.33	0.33	0.33
LBAI	0.80	0.10	0.10	0.80	0.10	0.10
MBRG	0.80	0.10	0.10	0.80	0.10	0.10
MOFG	0.80	0.10	0.10	0.80	0.10	0.10
MSL	0.80	0.10	0.10	0.80	0.10	0.10
MTB	0.80	0.10	0.10	0.80	0.10	0.10
NBTB	0.80	0.10	0.10	0.80	0.10	0.10
NRIM	0.80	0.10	0.10	0.80	0.10	0.10
ONB	0.80	0.10	0.10	0.80	0.10	0.10
PVTB	0.80	0.10	0.10	0.80	0.10	0.10
QCRH	0.80	0.10	0.10	0.80	0.10	0.10
RBCA	0.80	0.10	0.10	0.80	0.10	0.10

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RNST	0.80	0.10	0.10	0.80	0.10	0.10
SASR	0.80	0.10	0.10	0.80	0.10	0.10
SF	0.10	0.10	0.80	0.10	0.10	0.80
SHBI	0.10	0.10	0.80	0.33	0.33	0.33
SNV	0.80	0.10	0.10	0.80	0.10	0.10
SRCE	0.80	0.10	0.10	0.80	0.10	0.10
STI	0.10	0.80	0.10	0.33	0.33	0.33
THFF	0.18	0.72	0.10	0.10	0.80	0.10
TMP	0.16	0.10	0.74	0.10	0.10	0.80
TRMK	0.10	0.80	0.10	0.10	0.80	0.10
UBSI	0.80	0.10	0.10	0.80	0.10	0.10
UMBF	0.80	0.10	0.10	0.80	0.10	0.10
UMPQ	0.80	0.10	0.10	0.73	0.17	0.10
USB	0.80	0.10	0.10	0.80	0.10	0.10
VLY	0.80	0.10	0.10	0.80	0.10	0.10
WASH	0.10	0.80	0.10	0.80	0.10	0.10
WBS	0.10	0.80	0.10	0.10	0.80	0.10
WFC	0.10	0.80	0.10	0.80	0.10	0.10
BDGE	0.10	0.90	0.00	0.10	0.90	0.00
FCCY	0.15	0.85	0.00	0.67	0.33	0.00
FNLC	0.86	0.14	0.00	0.90	0.10	0.00
FRBK	0.15	0.85	0.00	0.67	0.33	0.00
HBNC	0.89	0.11	0.00	0.90	0.10	0.00
HTBK	0.63	0.37	0.00	0.90	0.10	0.00
PMBC	0.86	0.14	0.00	0.90	0.10	0.00
UNTY	0.10	0.90	0.00	0.10	0.90	0.00
WABC	0.89	0.11	0.00	0.90	0.10	0.00

Table A1.4: Subunits' efficiency scores $\boldsymbol{e_{R_K 0 j_0}}$ and weights for subunits $\boldsymbol{W_{R_K j_0}}$ (year = 2010)

BHC	$W_{R_1 j_0}$	$W_{R_2 j_0}$	$W_{R_3 j_0}$	$e_{R_1 j_0}$	$e_{R_2 j_0}$	$e_{R_3 j_0}$
ACNB	0.12	0.16	0.73	0.97	1.00	0.27
AMNB	0.80	0.10	0.10	0.14	0.76	1.00
AROW	0.70	0.20	0.10	0.14	0.52	0.80
ASB	0.12	0.78	0.10	0.95	0.35	0.47
BAC	0.10	0.10	0.80	1.00	1.00	1.00
BANF	0.80	0.10	0.10	0.12	0.10	0.22
BANR	0.80	0.10	0.10	0.14	0.16	0.31
BBT	0.11	0.10	0.79	1.00	0.83	0.19
BMTC	0.80	0.10	0.10	0.12	0.31	0.58
BOH	0.10	0.80	0.10	1.00	0.24	0.10
BOKF	0.10	0.80	0.10	0.75	0.22	0.67

BPOP	0.80	0.10	0.10	0.18	0.70	0.74
BXS	0.12	0.10	0.78	0.53	0.20	0.14
C	0.10	0.10	0.80	1.00	0.32	1.00
CBSH	0.10	0.80	0.10	0.94	0.10	0.29
CBU	0.80	0.10	0.10	0.13	0.39	0.19
CCNE	0.80	0.10	0.10	0.14	0.84	0.64
CHFC	0.80	0.10	0.10	0.16	0.26	0.21
CMA	0.80	0.10	0.10	0.25	1.00	0.47
COF	0.80	0.10	0.10	0.26	0.88	0.14
COFS	0.10	0.10	0.80	1.00	1.00	0.34
COLB	0.80	0.10	0.10	0.14	0.60	0.18
CSFL	0.11	0.79	0.10	0.45	0.06	0.25
CTBI	0.80	0.10	0.10	0.17	0.39	0.26
CZNC	0.78	0.12	0.10	0.15	1.00	0.76
DFS	0.80	0.10	0.10	0.34	0.01	0.55
EFSC	0.80	0.10	0.10	0.17	0.50	0.59
EWBC	0.80	0.10	0.10	0.30	0.35	0.10
FCF	0.80	0.10	0.10	0.13	0.79	0.24
FCNCA	0.80	0.10	0.10	0.14	0.04	0.10
FFKT	0.10	0.80	0.10	0.99	0.11	0.39
FHN	0.10	0.10	0.80	0.40	0.83	0.26
FIBK	0.11	0.79	0.10	1.00	0.32	0.12
FISI	0.40	0.50	0.10	0.28	0.22	0.44
FITB	0.80	0.10	0.10	0.21	0.78	0.57
FMNB	0.80	0.10	0.10	0.14	0.84	0.76
FULT	0.80	0.10	0.10	0.17	0.74	0.06
GABC	0.11	0.79	0.10	0.91	0.40	1.00
HBAN	0.80	0.10	0.10	0.14	0.54	0.41
HOMB	0.80	0.10	0.10	0.18	0.28	0.36
INDB	0.80	0.10	0.10	0.13	0.67	0.26
KEY	0.10	0.80	0.10	0.77	0.11	0.67
KTYB	0.80	0.10	0.10	0.14	0.81	1.00
LBAI	0.80	0.10	0.10	0.17	0.64	0.44
MBRG	0.80	0.10	0.10	0.09	0.38	0.49
MOFG	0.80	0.10	0.10	0.13	0.60	0.63
MSL	0.80	0.10	0.10	0.13	0.43	0.62
MTB	0.80	0.10	0.10	0.20	0.97	0.30
NBTB	0.80	0.10	0.10	0.13	0.53	0.56
NRIM	0.80	0.10	0.10	0.13	0.38	0.79

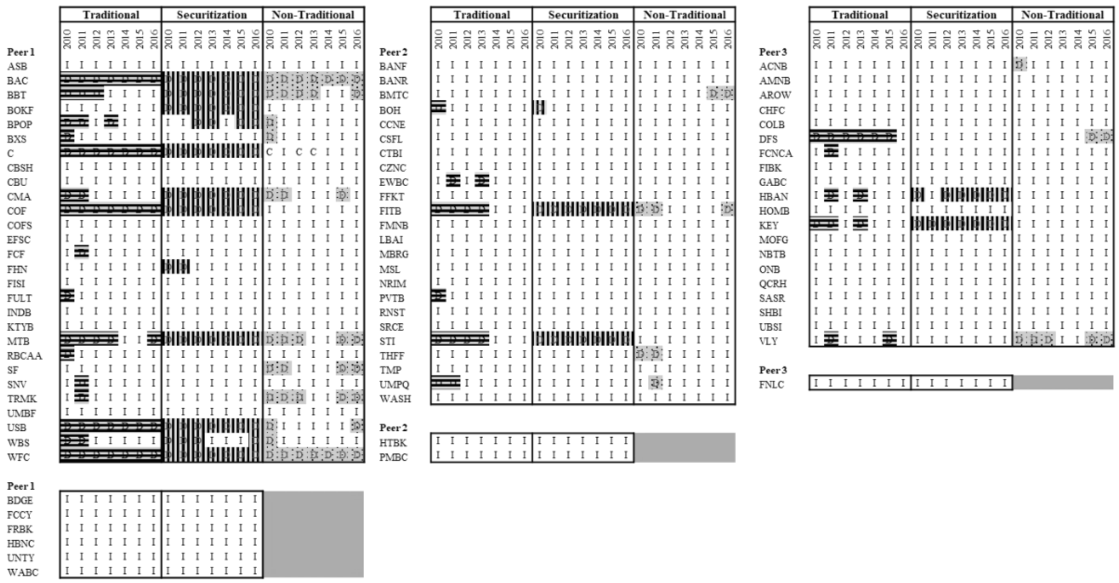
ONB	0.80	0.10	0.10	0.09	0.49	0.80
PVTB	0.80	0.10	0.10	0.15	0.88	0.43
QCRH	0.80	0.10	0.10	0.12	0.30	0.61
RBCA A	0.80	0.10	0.10	0.18	0.52	0.23
RNST	0.80	0.10	0.10	0.12	0.50	0.31
SASR	0.80	0.10	0.10	0.12	0.56	0.68
SF	0.10	0.10	0.80	0.02	0.03	0.18
SHBI	0.10	0.10	0.80	0.88	0.39	0.25
SNV	0.80	0.10	0.10	0.13	0.41	0.14
SRCE	0.80	0.10	0.10	0.13	0.31	0.38
STI	0.10	0.80	0.10	0.86	0.10	0.91
THFF	0.11	0.79	0.10	0.96	0.14	0.84
TMP	0.12	0.10	0.78	0.58	0.74	0.15
TRMK	0.10	0.80	0.10	1.00	0.12	1.00
UBSI	0.80	0.10	0.10	0.18	0.65	0.16
UMBF	0.80	0.10	0.10	0.11	0.48	0.46
UMPQ	0.77	0.13	0.10	0.14	0.90	0.22
USB	0.80	0.10	0.10	0.18	0.71	0.22
VLY	0.80	0.10	0.10	0.20	1.00	0.47
WASH	0.11	0.79	0.10	0.79	0.26	0.45
WBS	0.10	0.80	0.10	0.96	0.19	0.19
WFC	0.61	0.29	0.10	0.74	1.00	1.00
BDGE	0.10	0.90	0.00	0.89	0.18	0.00
FCCY	0.15	0.85	0.00	0.56	0.12	0.00
FNLC	0.87	0.13	0.00	0.16	0.47	0.00
FRBK	0.15	0.85	0.00	0.61	0.14	0.00
HBNC	0.89	0.11	0.00	0.13	0.59	0.00
HTBK	0.74	0.26	0.00	0.14	0.55	0.00
PMBC	0.87	0.13	0.00	0.11	0.54	0.00
UNTY	0.10	0.90	0.00	1.00	0.14	0.00
WABC	0.89	0.11	0.00	0.19	0.54	0.00

Appendix 1.7

Returns to scale (RTS) analysis.

Free signs μ_k^0 by subunits (across the three income-generating activities) and peer-groups are presented. The letter “D” represents decreasing RTS and the letter “I” refers to increasing returns to scale (RTS).

Figure A1.1: Free sign $\boldsymbol{\mu}_k^0$ by subunits



Appendix 2 Supplementary Materials for Chapter 3

Table A2.1: Measurement items and supporting literature

Measurement items	Source
Capability to Digitize Retail Banking Services (CAP)	
CAP1: My retail bank/credit union continually integrates emerging digital technologies (e.g., AI, blockchain, cloud-based computing) to allow existing retail banking services to be offered digitally.	Capability to digitize retail banking services is measured with a newly developed, 4-item measurement scale. We model the four measurement items after the "*eBusiness Capability*" measurement scale from Devaraj, Krajewski, and Wei (2007), which assesses the ability of a firm to use Internet technologies to support online business transactions with customers and suppliers, and after the "*IT Experience*" measurement scale from Menor and Roth (2007), which assesses the use of IT to support or improve inter-organizational coordination when developing new services.
CAP2: My retail bank/credit union consciously applies emerging digital technologies to enable existing retail banking services to be executed digitally by the customers.	
CAP3: My retail bank/credit union actively explores opportunities to deploy emerging digital technologies to convert existing retail banking services to be offered digitally without human interactions.	
CAP4: My retail bank/credit union regularly leverages emerging digital technologies to transform existing retail banking services into customer-executed services supported by technologies.	

<table>
<tr><td colspan="2">Response based on a 5-point, Likert-response scale. 1: very inaccurate, 3: Neither inaccurate nor accurate; 5: Very accurate</td></tr>
<tr><td colspan="2">Business Performance Improvement (PERF)</td></tr>
<tr><td>PERF1: My retail bank/credit union's acquisition of new customers from offering digital retail banking services is…</td><td rowspan="5">Business performance improvement is measured with a newly created, 5-item measurement scale, modelled after similar measurement scales from Vorhies and Morgan (2005), Vorhies, Morgan, and Autry (2009); and Narayanan, Jayaraman, Luo, and Swaminathan (2011) for business performance and market effectiveness.</td></tr>
<tr><td>PERF2: My retail bank/credit union's profitability from offering digital retail banking services is…</td></tr>
<tr><td>PERF3: My retail bank/credit union's operating cost reduction from offering digital retail banking services is …</td></tr>
<tr><td>PERF4: My retail bank/credit union's competitive positioning in the market from offering digital retail banking services is …</td></tr>
<tr><td>PERF5: My retail bank/credit union's market share growth from offering digital retail banking services is …</td></tr>
<tr><td colspan="2">Response based on a 5-point, Likert-response scale. 1: much worse than competitors, 5: much better than competitors)</td></tr>
<tr><td colspan="2">Front-office Back-office Process Alignment (FOBO)</td></tr>
<tr><td>FOBO1: Operational information is regularly exchanged between the front-office and the back-office.</td><td rowspan="4">Front-office back-office process alignment is measured with a 4-item measurement scale that adapts one measurement item from the “Internal integration” measurement scale in Schoenherr and Swink (2011), two from the “Internal Integration” measurement scale in Braunscheidel and Suresh (2009), and one from the “Process Integration” measurement scale in Narayanan et al. (2011).</td></tr>
<tr><td>FOBO2: The front-office and back-office personnel work as a team to solve process misalignment problems.</td></tr>
<tr><td>FOBO3: The front-office and back-office communicate frequently about their respective process goals and priorities to serve customers.</td></tr>
<tr><td>FOBO4: The front-office and back-office personnel work as a team to integrate their respective processes to serve customers.</td></tr>
<tr><td colspan="2">Response based on a 5-point Likert-response scale. 1: strongly disagree, 3: Neither agree nor disagree; 5: strongly agree</td></tr>
</table>

Table A2.2: Control variables definition, measures, and source of data

Control variables	**Definition**	**Measure**	**Source**
Retail banking unit type (RBU_TYPE)	The RBU is analyzed as a retail bank or a credit union	dummy variable, (=1, credit unions; =0, retail banks)	web-based survey
Number of digital offerings (D_OFFER)	The number of digital retail banking services offered by an RBU. Nine categories of digital retail	count value based on the number of digital retail banking services reported in the survey	web-based survey

	banking services are listed: digital account management, digital financing, digital money, digital payment, digital investment, digital insurance, digital security, digital financial planning, and digital advice		
Digitization age (D_AGE)	refers to the length of digitization of services offerings in the RBU	dummy variable, (=1, if the first digital retail banking services is offered before 2008; = 0, otherwise)	web-based survey
Established age (E_AGE)	refers to the age of the RBU	continuous variable, using the total number of years an RBU has been established	Google search & annual reports
Investment in the digitization of service offerings (INVEST)	refers to the investment the RBU has made into the digitization of retail banking services	categorical variable (= 1, less than 100,000; =2, 100,000 to 5 million; =3, more than 5 m)	web-based survey
Market turbulence (MAR_TUR)	refers to the change in customer preferences on retail banking services	measurement adapted from H. Liu et al. (2016)	web-based survey
Technology turbulence (TECH_TUR)	refers to the changes in new technologies used to support retail banking services in the industry	measurement adapted from H. Liu et al. (2016)	web-based survey

Table A2.3: The results for the mediator in Model 1 and results for PERF in Model 2

	Model 1 (OLS) CAP				Model 2 (OLS) PERF			
	Std. Estimates	S.E.	*p*-value	VIF	Std. Estimates	S.E.	*p*-value	VIF
IMP_CUST	0.322 ***	0.144	< 0.001	1.005				

FOBO	0.216 **	0.104	0.017	1.005				
Mediator								
CAP					0.383 ***	0.095	<0.001	1.141
Control								
RBU_TY								
PE					-0.214 **	0.152	0.019	1.175
D_OFFER					0.188 **	0.04	0.043	1.231
E_AGE					0.115	0.002	0.198	1.162
D_AGE					-0.022	0.127	0.798	1.101
INVEST					0.04	0.112	0.661	1.219
TECH_T								
UR					-0.048	0.066	0.618	1.321
MAR_TU								
R					-0.037	0.051	0.692	1.279

*** p<0.01, ** p<0.05, * p<0.10