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Analysis of Technological Learning and the
Learning Curve of Financial Institutions in Nigeria

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ABSTRACT

The objective of this thesis is to investigate whether bank's experience reduces both the cost of credit and value creation. The thesis also examines the social and economic impact of digital technological innovations (in the domain of payments system and electronic banking) on the Nigerian economy. Using data extracted from income statements and balance sheets of Nigerian commercial banks, I test for the effect of bank experience on the efficiency of credit and value creation. The findings indicate that bank experience significantly improves cost efficiency gain in credit creation and the gross value added to the economy. That is, bank experience improves the efficiency of lending to the real sector and service provisions. This implies learning by intermediating (investment and risk-taking). In addition, I use electronic payment systems (EPSs) data and survey data to forecast the diffusion of digital financial payments technologies, and to evaluate the socioeconomic impact and determinants of electronic banking in Nigeria, respectively. The findings indicate that digital payments technologies and electronic banking are widely diffused. The mobile payment technology is forecasted to dominate other payment technologies as the most diffused payment system in approximately a decade from now. Therefore, mobile payment technology could be a tool to drive financial inclusion and the cashless economy project in Nigeria. However, the finding also indicates that widespread electronic fraud has largely hindered the diffusion of electronic payment among small businesses.

The primary knowledge contribution of this thesis is the application of the learning curve to capture bank experience in credit and value creation – a context that has not yet been examined in the literature on organisational learning. This thesis, therefore, extends our understanding of the relationship between bank experience and performance improvement (defined by cost efficiency gain). The findings of this study are useful to bank managers in their evaluation of cost dynamics in bank credit creation (risk management and lending to the real sector), and to regulators in their evaluation of financially developed banks (efficient banks). The findings are also important for policymakers and regulators in their evaluation of digital financial technologies, the socioeconomic impact of financial technologies, and the challenges of electronic banking in Nigeria.

Dedication

This thesis is dedicated to my wife (Eunice), my lovely kids (Barachiah and Benaiah), my Father (Francis), and my mother (Mary).

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First, I would like to thank the Japan Society for the Promotion Science (JSPS) whose financial support and generous research grants made this research successful. Second, I would like to thank the graduate school office of Ritsumeikan University for the award of *KENKYU-SHOREI scholarship S* that eliminated my tuition, removed the financial burden off my shoulder, and enabled me to focus on my research. Third, I would like to thank my Supervisor, Professor Izawa Hiroshi, whose direction and comments shaped the content of this work. Furthermore, comments from conference participants and anonymous journal reviewers have improved the quality of this work. All errors and opinions are mine. Finally, I thank family and friends for their emotional support.

Declaration

I declare that all the material contained in this dissertation is my work. All secondary sources have been appropriately acknowledged and cited. This thesis has not been submitted for a degree at another university.

Chapter 1

1.1. Background of the study

Financial development, as measured by the lower cost of producing financial services, can be determined by bank's *experience* (hereafter, simply 'bank experience'). This experience may be garnered from sustained efforts in the value addition processes, continuous monitoring and screening of potential borrowers, or from the information-intensive processes involved in asset transformation, such as investment and risk management, that yield earning assets for banks. The efficiency gains from experience could lead to a decline in the amount of monitoring labour (cost) required for the same volume of loans. This happens as the bank recognises what information is crucial and sufficient for efficient monitoring, or as more effective screening technologies and characteristics of the applicant population are learned over time (Bush, 2015). Most importantly, from policy perspectives, one may argue that 'to the extent that financial firms can capture knowledge gained from experience, changing processes, and organisational structure, policymakers would not want these experienced firms to disappear' as this could lead to the loss of information capital (i.e. information on existing borrowers) which has been adequately captured in these financial firms (Bush, 2015).

Furthermore, given the volatile and competitive nature of the banking industry, bank experience has been found to significantly; improve performance when competition triggered learning (Barnett et al., 1994), reduce failure rates when merger-acquisition triggered knowledge integration and codification (Zollo & Singh, 2004), improve CAMEL ratings when survival enhancing learning resulted from both success and failure experience (Kim et al., 2009), and improve cost efficiency when learning resulted from operating experience (Bush, 2015).

The above descriptions parallel learning-by-doing, defined as a mechanism that reduces the costs of production by leveraging the experience gained in the production processes. This phenomenon has been quantified using the learning curve theory. This theory says that the logarithm of unit cost decreases with the logarithm of cumulative output at a uniform rate called the learning rate (Lapr   & Van Wassenhove, 2001).

The learning curve phenomenon has been studied extensively in many organisations. However, there has been limited application in financial service organisation such as banks. The difficulty with applying the learning curve theory to banks lies in the fundamental definition of output in banks. Defining the unit of service in banks to operationalise experience for measuring the relationship between cumulative experience (knowledge acquired through bank intermediation and asset transformation) and productivity is difficult. This is a significant undertaking of this thesis.

1.2. Motivation and importance of the study

Banks remain the principal source of financial intermediation and channels of making payments. Thus, banks play an important role in economic development (Paradi & Zhu, 2013). A strong banking sector effectively channels funds and other financial products from surplus economic agents to deficit economic agents, and thus, stimulates the finance growth nexus seen in the local economy. A fragile and weak banking sector is also a catalyst for economic regress or stagnation. This positional advantage of banks has made them the engine of growth and development, especially for developing economies, and underscored the need for sound, strong, and financially developed banking sector (Sharma et al., 2013). Furthermore, this has made bank performance one of the most studied issues in literature.

The literature contains many empirical methods, grounded in finance and economic theories, for measuring bank performance. However, from the organisational learning literature, the relationship between bank experience in credit creation (lending to the real sector and managing risk), value creation (economic profit created and gross value added), and cost efficiency gain (performance) has not been given adequate attention.

Furthermore, the Nigerian context presents an interesting setting to investigate the relationship between bank experience and cost efficiency gain in credit and value creation for three reasons: (1) The banking sector is one of the fastest-growing sectors in Nigeria in terms of contribution to gross domestic product (GDP; National Bureau of Statistics, 2020); (2) As a developing economy with a weak financial market, the banking sector is the primary source of credit to the private sector. Furthermore, the link between bank

lending (credit) to the private sector and economic development in Nigeria has been positively established in the literature (Akujinma et al., 2017; Eburajolo & Aisien, 2019; Eugenia et al., 2018; Innocent et al., 2019); and (3) Financial development driven by bank sector reforms remains the top policy experiment in Nigeria. Therefore, policymakers (including bank managers) need adequate tools to develop appropriate monetary policies to improve the productivity of the nation's banks. All these points underscore the need for this research.

1.3. Purpose and Research Questions

This thesis has two main purposes: First, it investigates whether bank intermediary experience is correlated with cost efficiency gain and improved performance. To achieve this, I classify bank production according to the two major roles performed by banks: credit and value creation. The rationale is that as bank accumulates experience in the information-intensive process of credit and value creation, this experience creates knowledge that may improve productivity. Second, I investigate the diffusion of digital financial technologies and the determinants and challenges of electronic bank learning and adoption in Nigeria. This is important given the proliferation of emerging financial technologies and the impact of these technologies on Nigeria's social and economic strata. The key research questions addressed in this thesis are as follows:

1. Does bank experience improve the efficiency of credit creation (lending to the real sector, investments, and risk-taking)?
2. Does bank experience improve the efficiency of value creation (shareholder value and gross value added to the economy)?
3. What is the current level of diffusion and future trajectories of some financial technologies in Nigeria?
4. What are the determinants (social and economic) and challenges facing diffusion/adoption of financial technologies and electronic banking in Nigeria?

1.4. Findings of the study

Using a cost function that incorporates learning, the findings of the first part of this thesis indicate that bank experience improves the efficiency of credit creation. That is,

experience lowers the unit cost of producing additional credits. The findings also indicate that experience improves the efficiency of the gross value added to the economy. That is, experience lowers both the unit cost of lending to the real sector and the service provisions. However, the efficiency gains from experience in gross value added were interrupted at some points due to shocks in the economy. In terms of shareholder value created, the findings indicate that experience does not improve the shareholder value created. That is, experience does not lower the unit cost of producing economic value added (EVA). This may imply that shareholder value was substantially destroyed in Nigerian commercial banks.

The findings of the second part of this thesis indicate that the diffusion of some major electronic payment technologies is widespread in Nigeria and is forecasted to last several years into the future. The mobile payments system, in particular, is forecasted to emerge as the most diffused financial technologies in Nigeria going forward. However, the findings also indicate that widespread electronic fraud limits person-to-person adoption/diffusion of electronic payments. This is a setback for the cashless economy project. It is also a setback to the financial inclusion efforts of the Nigerian government.

1.5. Contributions of the study

The above findings contribute to the literature in three broadways.

First, the theory of organisational learning has been applied to many organisations but has found limited applications in banks. The analyses in this thesis contribute to the debate on how bank experience can contribute to financial development, improve financial performance, and reduce bank failure rate (Barnett et al., 1994; Bush, 2015; Kim et al., 2009; Zollo & Singh, 2004). In particular, the framework and the research method that applies the learning curve to model bank experience in this research is a major contribution in the context of organisational learning literature. Furthermore, operationalising and defining the unit of experience, that allows for empirical estimation of the relationship between unit cost and outputs in banks, contributes to the literature in another unique way.

Second, the findings of this thesis contribute to the debate on the factors affecting the success of two recent monetary policies viz. the cashless economy and the financial integration strategy of the Nigerian government.

Third, the findings of this thesis contribute to the debate on the social and economic impact of the proliferation of financial technologies in developing countries where weak policies, poor digital infrastructure, and corporate malpractices have continued to weaken the financial economy.

1.6. Organisation of the Study

This thesis is broadly divided into two parts. Part one focuses on modelling the relationship between bank experience and cost efficiency gains using the learning curve developed from the theory of organisational learning. Part two focuses on technological learning in the Nigerian financial system. Specifically, the thesis is outlined as follows: Chapter 2 describes the structure of the Nigerian financial system, and reviews the structural changes shaped by policy reforms and information technologies. Chapter 2 also examines the extant literature on the evolution and proliferation of financial technologies in Nigeria. Chapter 3 presents the theory and applications of organisational learnings. Chapter 4 develops a framework and a research method for applying the learning curve to banks. Chapter 4 also defines and operationalises experience in banking that in turn allows for estimating the efficiency of credit and value creation in banks. Chapter 5 applies the developed framework to a sample of commercial banks in Nigeria, and presents and discusses the empirical results. Chapter 6 evaluates some major digital payment technologies. More specifically, Chapter 6 forecasts the diffusion of four digital payments system and analyses the competition between these technologies. Chapter 7 analyses the determinants, gains, and challenges of the adoption/diffusion of electronic banking among a large sample of respondents drawn using a field survey. Chapter 8 summarises the findings of the thesis, outlines the implications, and provides policy recommendations. This chapter also highlights some limitations of the study and offers suggestions for future research.

Chapter 2

The Nigerian Financial System: Analysis of the Current Situation

2.1. Introduction

This chapter presents an overview of the Nigerian financial system. The chapter begins with a brief description of this system and the role it plays in local financial integration. The chapter also describes recent reforms, digital technology, and structural changes in the system. Finally, it reviews the literature on the social and economic impact of information and communication technologies (ICT), financial technologies, and electronic banking on the Nigerian economy.

2.2. The Nigerian financial system

The Nigerian financial system comprises formal financial institutions (commercial banks, insurance companies, development finance, and agricultural cooperatives banks), financial markets (money and capital markets), primary mortgage institutions, and informal institutions (Bureau de exchange, local money lenders, and saving associations). The single most important financial institution in Nigeria are the commercial banks, largely dominated by Deposit Money Banks (DMBs). These institutions perform three major roles vital for economic growth and development in Nigeria, namely working as convenient and efficient payment systems, lending to the real sector by utilising savings from surplus economic agents, and productive investment and risk mitigation (CBN, 2017b).

The rising demand for financial resources due to the growing population, inadequate formal financial resources offered by the formal financial institutions, and stringent lending conditions in the formal financial institutions necessitated reliance on the informal finance sector. This is a sector that long predates the formal sector and was thought to have ceased operation. Two famous informal finance sectors are the local money lenders and the savings associations, both of which operate in a shadow economy and whose activities are largely unregulated. Lending activities in these sectors are uncollateralised and are primarily based on interpersonal connections and reputation, or trust between the lender and the borrower. This makes monitoring and enforcement of

repayment relatively easier than formal financial institutions (Adeleke, 2014). According to Adeleke (2014), this sector (informal sector) accounts for 85% of rural savings and credit in Nigeria.

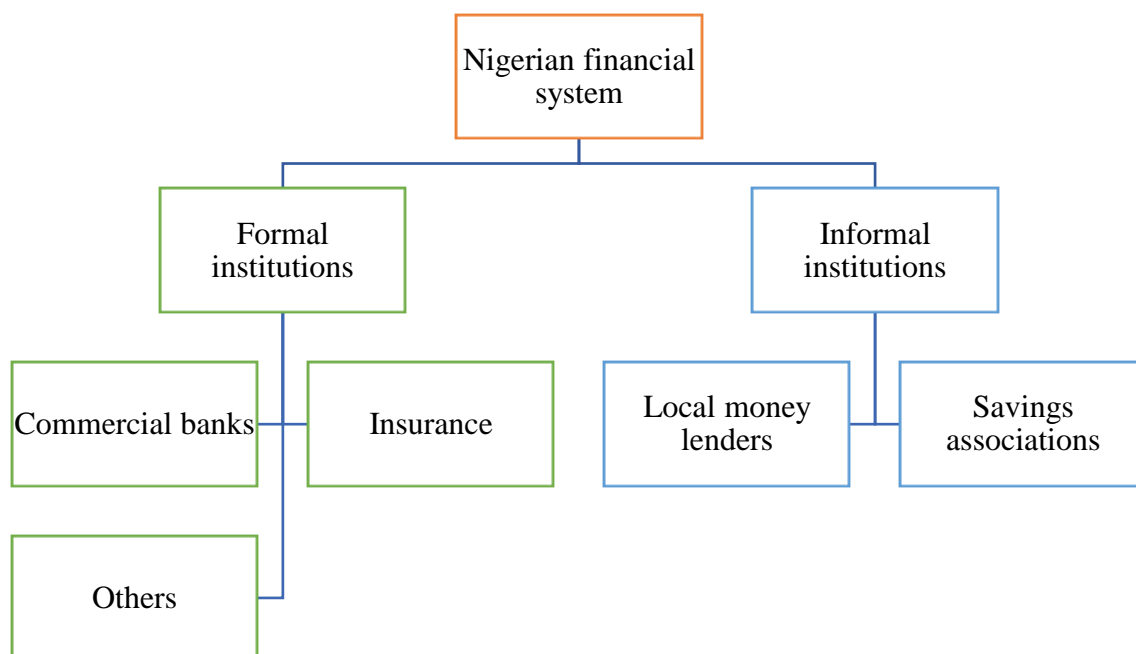


Figure 2.1. Structure of Nigeria's financial system.

2.3. Financial reform, technology, and structural changes in Nigeria

Formal financial institutions are regulated by the central government through the Central Bank of Nigeria (CBN) and other regulatory agencies. This sector has witnessed considerable reforms geared towards repositioning it for efficient performance. One famous reform was the consolidation and recapitalisation of banks introduced in 2004. This reform transformed commercial banks in Nigeria into 'megabanks', where diversified, strong, and reliable banks that can guarantee the safety of customer deposits and contribute to the growth of the Nigerian economy were allowed to continue in business (CBN, 2004). This reform was a revolution that completely changed the ownership structure, financial instruments, the regulatory and supervisory framework, and the macroeconomic environment of financial institutions in Nigeria. Most importantly, the 2004 reform targeted volatile and inefficient banks, and significantly reduced the number of established financial institutions by 60%. In hindsight, this policy

has been described as a ‘huge success’, and a case has been made for further consolidation (Umoren & Olokoyo, 2007; Adegaju & Olokoyo, 2008; Clementina & Isu, 2014; Muritala et al., 2018).

To align Nigerian banks to emerging technological changes and financial innovations, and to reduce the cost of cash handling, the cashless policy was introduced in 2011 by the CBN. The major thrusts of the cashless policy according to the CBN include reducing cash transaction cost by 30%, increasing access to financial services, and enabling financial integration and inclusion that will stimulate economic growth and development (Atanda & Alimi, 2012; CBN, 2011). This policy created, encouraged, and pushed for the adoption of electronic payment systems (EPSs) among all stakeholders as against physical cash payment. This was done by placing unpalatable cash handling charges for withdrawals above a daily limit for both individual and corporate account holders. The cashless policy was systematically implemented across Nigerian states, starting from Lagos state, the largest industrial hub of Nigeria, and later to all other states in the later phases of implementation (CBN, 2014, 2017a).

Transitioning to an efficient cashless economy implies robust, sound, and secure payment systems. As a result, the CBN in collaboration with bankers committee and other stakeholders in the demand and supply side of the chain devised robust payment systems suitable for all actors, considering all possible challenges of the cashless alternative payments system. This led to the introduction of the mobile payment system in 2010. This policy was designed to liberalise the digital financial ecosystems by including new players and improve financial inclusion. Along with this, other policies were subsequently revised with the emergence of new financial technologies and payment platforms believed to have the added advantage of ensuring efficient, secure, and transparent transactions for end-users (CBN, 2018a, 2019; Obaigbona, 2010). In what followed, myriads of payments system were created, advanced, and propagated between 2012 till date.

This digital transformation in the Nigerian financial sector is not without challenges. For example, the enabling policies in electronic banking clearly define the roles of service, technology, and infrastructural providers (i.e. banks, telecom companies, and software

developers) in meeting the need and protecting the interest of end-users. However, evidence from an official conflict resolution desk, the Nigeria Electronic Fraud Forum (NeFF), shows that the end-users are largely exposed to electronic fraud and have lost chunks of money via e-banking. For example, NeFF reported more than 19,000 fraud cases in 2016, an 82% increase over 2015 and 1200% over 2014 reported cases (NeFF, 2016). More recently, NeFF reported a total of 1.6 billion-naira lost from approximately 25,043 cases of e-fraud (CBN, 2018a). There are also cases of e-fraud not officially registered due to victim's unawareness of avenues to pursue their case.

2.4. The evolution of electronic bank learning in Nigeria

The emergence of electronic banking in Nigeria perhaps began after the 1986 deregulations that liberalised bank licensing and opened avenues to a new generation of entrants with innovative products and services in contrast to the 'arm-chair brick and mortar' services rendered by existing banks. Taking advantage of existing and emerging technologies, the new generation of banks opted for automation of service deliveries, computerisation of bank activities, and the continuous introduction of new products and services in response to customer needs and sophistication. The result was intense competition, and process, product, and service innovations that completely transformed the Nigerian financial space (Agboola, 2003; Oluwatolani et al., 2011; Ugwu et al., 2000). Decades later, the diffusion of these technologies and service innovations brought new financial technologies, created new payment systems, and established digital financial ecosystems as actors in the chain continually demand new and better services tailored to their needs and convenience. As the demand for e-banking technologies and services grew, banks and financial institutions in Nigeria responded aggressively, prompting the CBN to implement several guidelines and measures for secure e-banking in its different components and platforms, and to stabilise, standardise, and maintain tight regulation. The earliest technologies and services deployed included GSM banking, home banking, ATM, smart card, pass card, and dial-up banking. The different EPSs and channels in existence in Nigeria today are the resultant effects of the decade-long learning-by-doing in the digital financial services experimentation in Nigeria.

2.5. The socioeconomic impact of the proliferation of electronic banking in Nigeria

The earliest study on the impact of ICT on banks and insurance was done by Ugwu et al. (2000). The authors showed empirical evidence on how ICT has improved productivity and how it has been gaining momentum in the Nigerian financial space. Acha (2008) enumerated the emerging electronic banking platforms and payment channels available between the late 1980s and the early 2000s. The author showed the usefulness and the new challenges these channels presented. Similarly, Adewuyi (2011) described the emergence of other electronic banking to include automated delivery channels such as home link banking, online banking, bankers automated clearing system (MICR), etc. Joseph and Richard (2015), and Adu (2016) updated earlier descriptive studies on e-banking with the introduction of newer payment systems such as real-time gross settlement (RTGS), Nigeria interbank settlement scheme (NIBSS), mobile money, and web-payment that have enabled the introduction of the cashless policy.

As digital banking spread across the length and bread of Nigeria, scholars began looking into the social and economic consequences of it on both banks and users. For example, focusing on mobile banking, Bankole et al. (2011) applied the revised unified theory of use and acceptance of technology (UTAUT) to a sample of 230 mobile banking adopters to understand the significant constructs drawn from a pool of theoretical constructs in the case of Nigeria e-banking users. Testing several hypotheses using structural equation modelling, the authors established that uncertainty, trust, ease of use, user satisfaction, and utility value significantly influence users' decision to adopt mobile banking. Similarly, Agwu and Carter (2014) studied mobile phone banking services in Nigeria using a structured questionnaire and focused group discussions on a sample of respondents. This study, although it relied on the descriptive analysis of a very limited sample of respondents, found that convenience, security, reduced cost, and higher penetration are among the benefits of mobile phone banking. The authors, however, cited poor mobile technology infrastructure as a major concern for mobile banking adoption. In another similar study, Olasina (2015) specifically evaluated factors affecting the adoption of mobile banking among academics in the University of Ilorin, Nigeria. By applying the so-called UTUAT approach and using an econometric model, the author showed that factors such as customer satisfaction, usefulness, ease of use, ICT skills, and

type of bank significantly influence the academics' decision to adopt and use mobile banking.

Other studies on the socioeconomic impact of e-banking on users in Nigeria focused on 'online banking' (i.e. bank apps or website accessible with internet-enabled devices). For example, Tarhini et al. (2015) qualitatively analysed responses from a small sample of 30 respondents (drawn from both users and non-users of online banking) using functionality constructs (awareness, accessibility, and ease of use), risks (trust, privacy, and security) and other constructs (culture, relative advantage, support, and knowledge and literacy level). The authors showed that these constructs are determinants of adoption of online banking in Nigeria, while poor internet infrastructure, trust, and security concerns are the major limiting factors in the adoption of online banking in Nigeria. Similarly, Okeke et al. (2015) analysed customer satisfaction with online banking services within the framework of service quality dimensions. Using correlation analysis and econometric models, the authors established that a significantly higher fraction of the 258 respondents had enhanced satisfaction in areas such as price, security, perceived risk, responsiveness, and assurance, but were dissatisfied with reliability and tangibility.

From the organisational and economic growth point of view, the adoption and proliferation of e-banking services have also been linked to improved operational efficiency and productivity of banks and financial institutions in Nigeria. Taiwo and Agwu (2017) used the Pearson correlation to investigate the impact of e-banking on the operational efficiency of four banks (Ecobank, UBA, GTBA, and First Bank) in Nigeria. Their results showed that the introduction of e-banking services significantly improved the revenue, capital base, and customer loyalty of these banks. Relatedly, a recent study that sought to evaluate the impact of e-banking on financial inclusion undertaken by Ene et al. (2019) used econometric analysis to test two hypotheses on the impact of e-banking, defined in terms of the number of installed ATMs and POS, on the attainment of the Nigerian government's financial inclusion goal. The authors established that the trend in the number of point of sale (POS) had a significant impact on financial inclusion (defined as the ratio of banked adult to bankable adult).

2.6. Concluding remarks and future direction

The discourse so far revealed three crucial findings. First, the Nigerian financial services industry, and in particular the commercial banks, is largely underdeveloped and needs critical evaluation that could inform further policy consolidations. Second, the fusion of technology and innovation with banking operations and services (technological learning) is still new and growing in the Nigerian financial space. Third, digital banking has generated enormous interests from both academics and policymakers because of the huge economic development potential it holds. Yet, several gaps exist in the literature, especially in the light of technological learning in the Nigerian financial sector. For example, what is the role of learning in cost efficiency gain in Nigeria's commercial banks? Furthermore, with the proliferation of financial technologies and payment platforms, some policy questions emerge: to what extent are these technologies adopted/diffused nationwide/what is the current level of diffusion of some financial technologies in Nigeria? How long do these technologies take to reach their saturation point? Given the heterogeneity of the Nigerian population, what are the factors (social and economic) that determine the adoption/diffusion of electronic banking?

To provide answers to these questions, I proceed as follows: First, in Chapter 3, I derive a framework based on the learning curve theory, and as a basis to evaluate the efficiency of credit and value creation in Nigerian commercial banks. This gives insight into how Nigerian commercial banks contribute to the real sector in terms of lending to the real sector, and how shareholders are being compensated for their risky investment. This will be the focus of Chapters 4 and 5, respectively. Second, I apply the technology forecasting model (growth model) in Chapter 6 to forecast the growth of EPSs in Nigeria. Finally, in Chapter 7, I develop a framework based on the theory of Generalised Structural Equation Modelling (GSEM) and describe the socioeconomic determinants of electronic banking adoption (diffusions) among a large sample of users drawn using a field survey.

Chapter 3

Literature Review on the Learning Curve: Theory and Applications

3.1. Introduction

The learning curve, proposed by Wright (1936) and by Arrow (1962), was used to quantify cost reductions in the form of changes in unit inputs (labour, capital, or intermediate goods) required in the production process. These changes that are not attributable to fluctuations in prices of variable inputs or economies of scale could be explained by the efficiency gain over time in the production process (Aduba & Asgari, 2020). This efficiency gain has been linked to knowledge gained from experience with routines of the production tasks, information sharing, re-engineering and redesigning, efficient production scheduling, efficient supply chain management, and strategic decision making. This phenomenon is well documented in industry and has been described in the literature as *learning-by-doing* (Arrow, 1962; Bahk & Gort, 1993; Balasubramanian & Lieberman, 2010; Irwin & Klenow, 1994; Levitt et al., 2013).

Factors that contribute to learning by doing in organisations are diverse. However, the *knowledge* generated during the production or service process seems to be the most crucial factor in organisational learning. This knowledge, scholars argued, might turn out to be a sustainable competitive advantage of the firm or organisation (Argote & Ingram, 2000). Furthermore, this knowledge (*appearing in various forms: know-what, know-how, know-why, and know-who*) could result from within or outside the organisations and could either be process improvement or product innovations, that is, improvement in product/service quality or both (Bahk & Gort, 1993; Darr et al., 1995). Still, other deliberate actions such as managerial levers could also accelerate the learning process in organisations. These levers may include direct labour training, engineering changes, or setting up specific research and development (R&D) units to create technological knowledge about a production function through some simple or rigorous scientific experiments (Lapr   & Van Wassenhove, 2001). In summary, the basic principle behind the learning curve is that production experience creates knowledge that improves productivity (Argote, 2012; Arrow, 1962). This chapter reviews the theory and

applications of the learning curve, intending to lay the groundwork for a new framework that would allow for its application in the banking sector.

3.2. The Learning (Experience) Curve: Theory

Improvements in efficiency of producing outputs from existing technologies and inputs are important sources of total factor productivity (TFP) growth. This productivity improvement could be explained by experience or knowledge acquired through learning by doing. This particular knowledge (experience) allows for product or process improvement in organisations and enables organisations to produce more output from a product or service with a significant decrease in the unit cost of production (Argote, 2012; Levitt et al., 2013). This process has been found to exist in many organisations and industries, and has been described in the literature as the 'learning curve'. As illustrated in Figure 3.1, the learning curve suggests that the unit cost of production decreases at a constant rate, called the learning rate, as output expands or doubles, that is, the average cost falls as more units of output are produced (Aduba & Izawa, 2020; Besanko et al., 2013; Karaoz & Albeni, 2005). The cause of this phenomenon, after controlling for fluctuations in prices of variable inputs and other factors, are generally linked to the effect of learning by doing. That is, the gain or advantages that flow from accumulating experience and technical know-how about the production process.

It is important to differentiate between economies of learning and economies of scale. Economies of scale or increasing return to scale are defined with respect to labour and capital only, and not the state of knowledge or technology in the production function. Learning, however, is concerned with efficiency resulting from the stock of knowledge (and technology) that can shift the average cost curve downward (see Figure 3.1). More precisely, learning economies imply reductions in the unit costs due to accumulating experience and is independent of the current scale of activity. Meanwhile, scale economies refers to reductions in unit costs due to large scale production at a particular point in time (Besanko et al., 2013).

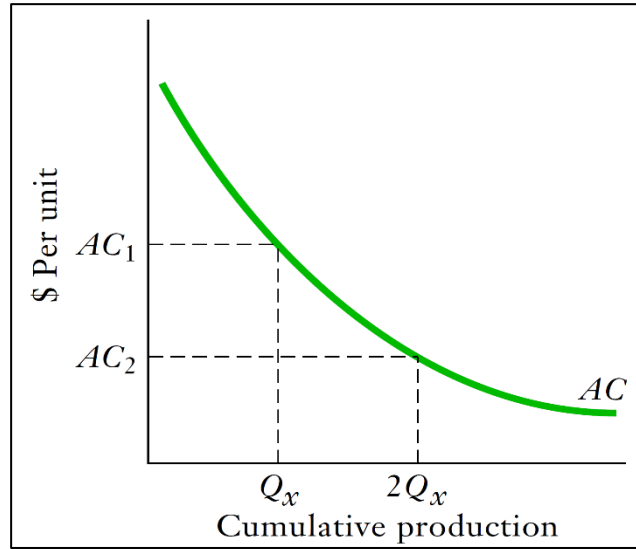


Figure 3.1. The learning curve (Source: Besanko et al. (2012))

3.3. The Learning Curve: Measurement and Estimation Strategy

The learning curve shows the extent to which firm or organisational performance improves with experience. This improvement or gain in experience, depending on the industry, is quantified using various learning models. In general, the power function (3.1) has been used to quantify learning in industries and organisations (Argote, 2012; Egelman et al., 2017; Levitt et al., 2013).

$$\tau_t = \theta \cdot X_t^{-\phi} \quad (3.1)$$

Where X_t is the cumulative number of units produced (i.e. a stock of knowledge or experience gained in the production process) at time t . τ_t is the cost required to produce an additional unit at time t . θ is the cost required to produce the first unit. ϕ is a parameter that measures the rate of change in unit cost as output expands and essentially describes the learning effect. t is the calendar time¹. Theoretically, $\phi < 0$ if learning occurs in the production process.

The log-linear form of equation (3.1) can be written as follows:

$$\ln \tau_t = \theta - \phi \ln X_t + e_t \quad (3.2)$$

¹ It is possible to separate organizational experience from external technological improvement. Including the calendar time, t , in the learning model will capture the general technological improvement in the external environment (Argote, 2012).

Where e_t is white noise.

As noted, learning in organisations is directly linked to productivity improvement. This is because knowledge acquired during the production process is cumulative and can be used to improve or speed up the production of additional units. This suggests there exists a relationship between the learning curve (equation (3.1)) and the Cobb-Douglas production function (equation 3.3) in terms of the Δ_t . Δ_t describes the current level of technology or the advances in knowledge base that could result from experience (cumulative production), written as equation (3.4).

$$Q_t = \Delta_t \cdot L_t^\alpha \cdot K_t^\beta \quad (3.3)$$

$$\Delta_t = \varphi X_t^\theta \quad (3.4)$$

Where Q_t is the output level at time t . L_t and K_t are labour and capital inputs respectively. α and β are the input elasticities for labour and capital, respectively. φ is a constant.

Equation (3.4) is similar to equation (3.1) and implies that the stock of knowledge, Δ_t , is directly proportional to cumulative output. Pramongkit et al. (2000, 2002) argued that as output expands, the relationship between labour and capital can be expressed as follows:

$$K_t = \mu L_t^\lambda \quad (3.5)$$

Where μ , and λ are constants.

As demonstrated by Pramongkit et al. (2000), Karaoz and Albeni (2005), and Aduba and Asgari (2020), the relationships between equations (3.3), (3.4), and (3.5) enable the characterisation of learning in organisations by a production function embedded in the traditional learning (experience) curve, which can be expressed as equation (3.6) and in log-linear form as equation (3.7)² as follows:

$$Y_t = \omega \cdot X_t^\phi \cdot L_t^\vartheta \quad (3.6)$$

$$\ln Y_t = \omega + \phi \ln X_t + \vartheta \ln L_t + e_t \quad (3.7)$$

² The proof of equation (3.7) has been given in Aduba and Asgari (2020) and has been reprinted in Appendix 3A part I.

Where $Y_t = (L/Q)_t$ is the unit labour (analogous of unit cost) required to produce an additional unit at time t , and ω is constant. All other parameters are as defined.

An alternative specification to measure the learning curve in organisations is to use the basic firm productivity model that incorporates learning, labour, and capital inputs, as proposed by Bahk and Gort (1993), and Egelman et al. (2017). This specification can be represented as follows:³

$$Q_t = \Delta_t \cdot G(X_t^\phi) \cdot L_t^\alpha \cdot K_t^\beta \quad (3.8)$$

$$\ln Q_t = \omega + \phi \ln X_t + \alpha \ln L_t + \beta \ln K_t + \delta t + e_t \quad (3.9)$$

Where t is the chronological time used as an approximation to capture productivity shift or the stock of knowledge Δ_t . This has been used to rule out alternative explanations of the learning effect. All other parameters are as defined.

In practise, depending on which output is employed and on the analyst's objective, equations (3.2), (3.7), and (3.9) are used for the empirical estimation of learning in organisations. However, because learning is dynamic, not static, a dynamic functional form of equations (3.2) and (3.7) has been derived based on the S-curve theory and used for studying the dynamics of learning in organisations (Aduba & Asgari, 2020; Badiru, 1992; Carlson, 1973; Karaoz & Albeni, 2005). This can be represented by equation (3.10) or by its empirical form in equation (3.11) as follows:⁴

$$Y_t = \omega \cdot L_t^\vartheta \cdot X_t^{i,\phi} \quad i=1,2,3 \quad (3.10)$$

$$\ln Y_t = \omega + \vartheta \ln L_t + \phi_1 \ln X_t + \phi_2 (\ln X_t)^2 + \phi_3 (\ln X_t)^3 + e_t \quad (3.11)$$

The nonlinear approach to the estimation of the learning curve (Figure 3.2) is useful as it adequately estimates the long-term annual technological progress ratio. Furthermore, this approach provides a sound framework for predicting the past and future path to technological forecasting (Karaoz & Albeni, 2005).

³ For simplicity, I eliminated other parameters in this model.

⁴ This is also called the cubic approximation to the learning curve. See Appendix 3A part II for the proof (reprinted from Aduba and Asgari (2020))

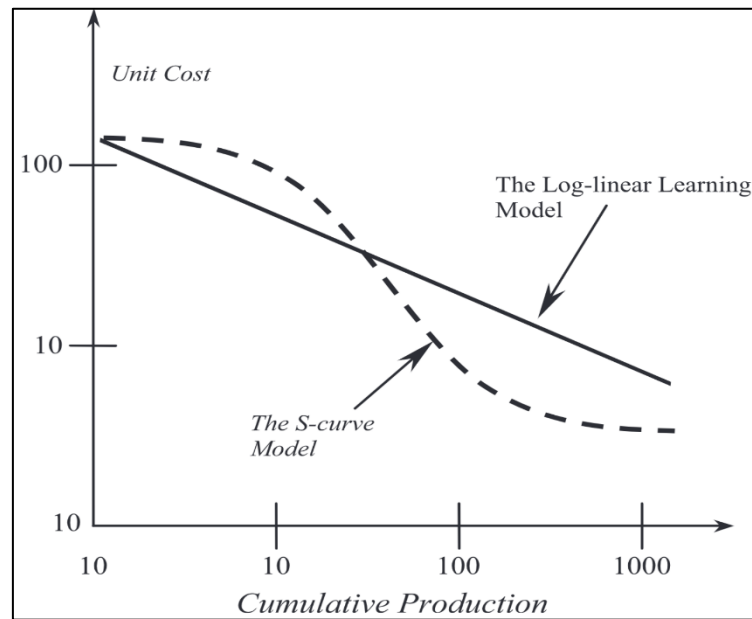


Figure 3.2. The S-curve and the learning curve in log-scales (Karaoz and Albeni (2005)).

3.4. The learning curve: Defining and measuring experience in organisations

Measuring organisational learning begins with defining and operationalising the learning concept. Several definitions of organisational learning existed in the literature. However, in the context of this research, the definition proposed by Fiol & Lyles (1985) appears to have the key elements needed. According to these authors, '*organizational learning is the process of improving actions through better knowledge and understanding*'. The productivity gains that stem from *improving actions through better knowledge and understanding* of the production or service process in organisations are significant (Argote, 2012).

Measuring this productivity gain through knowledge requires operationalising the knowledge term. Initially, the standard measure of knowledge or experience in the learning curve formulation is the cumulative number of units produced or services delivered, defined in terms of physical, tangible output or volume of shipment in factories. However, as literature on the learning curve advanced, other variants of outputs such as defect rate, quality, number of projects completed, TFP, and service time were used to measure learning by doing in both manufacturing and service organisations. This made it

possible for researchers to apply the learning curve to the length and breadth of organisations.

3.5. The learning curve's applications in manufacturing industries

Arguably, the theory and application of the learning curve began in the manufacturing of aircraft frames. Therefore, there are numerous applications of the learning curve in the manufacturing industries. For example, Egelman et al. (2017) applied the learning curve to high-technology hardware firms to measure productivity improvement from the knowledge acquired through experience. Using 10 years of weekly data on the volume of shipment from a firm's production and human resource tracking system, the authors operationalised production experience as the cumulative volume of shipment produced weekly.

Levitt et al. (2013) researched learning by doing in automobile assembly using the cumulative number of cars produced as a proxy for experience and found that the number of defect per car produced reduces as more cars were produced. The authors attributed this phenomenon to acquisition, aggregation, transmission, and embodiment of the knowledge stock built through learning. They argued that this can also be lost over time with poor management and other external factors. A similar study on creating and transferring knowledge for productivity improvement in factories by Lapré and Van Wassenhove (2001) used TFP as the proxy of experience to show that formal learning significantly drives productivity improvements. Consequently, they established that management buy-in and knowledge diversity may create and facilitate the transfer of technological knowledge. Many researchers have also used the cumulative number of units produced at organisational, factory, or plant level to study the learning curve of the respective industries.

In terms of financial productivity, Bahk and Gort (1993) used *valued-added* (measured in financial terms) and *volume of shipment* as proxies for experience, and found that both outputs adequately capture firm-specific learning in the sub-industries studied. Consequently, many other scholars have used value-added to study the learning curve in the manufacturing industry, especially at the 3-digit ISIC where data on shipments or

output quantities are difficult to find⁵. For example, using cumulative value-added (also measured in financial terms) as a proxy for experience, Pramongkit et al. (2000, 2002) studied productivity improvement as a function of technological learning in the Thai manufacturing industries. The authors found that productivity in some clusters of the Thai manufacture industries resulted from technological learning.

In a similar study, Karaoz and Albeni (2005) applied the learning curve to Turkish manufacturing industries to study technological learning using gross value added (also measured financial terms) to show that industries learn at different rates and time. Asgari and Yen (2009) studied dynamic technological learning in Malaysian manufacturing and service industries using value-added (also measured in financial terms) as a proxy for experience and found evidence of technological learning in both industries. More recently, Aduba and Asgari (2020) studied the productivity and technological progress of the Japanese manufacturing industries using gross value-added and found that learning is unique to an individual industry but has been declining in recent years.

3.6. The learning curve applications in the services industry

3.6.1. Non-financial services

The learning curve has also been applied to a variety of service industries using different experience terms. Darr et al. (1995) studied productivity in franchises via the lenses of acquisition, transfer, and depreciation of knowledge in service organisations. The authors used the cumulative value of pizzas produced as a proxy for experience and found that productivity was largely enhanced through knowledge acquired from experience (learning-by-doing). Baum and Ingram (1998) studied the learning curve of the Manhattan hotel industry using data on available rooms as the proxy for consumer's hotel experience. The authors found that organisational experience has a U-shaped effect on hotel experience and that organisations [hotels] enjoy reduced failure rate as a result of population experience before their founding. This suggests that learning from related organisations (hotels) lowers the failure rates of new ones.

⁵ ISIC stands for international standard industrial classification, a process which classifies industries in blocks of certain outputs.

The learning curve of a professional service organisation that uses information technology such as project Management System (PMS) and Computer-Aided Design (AUTOCAD) has also been studied. Boone and Ganeshan (2001) found that the effect of information technology on learning in a certain professional service organisation was significant. Controlling for the effect of these two technologies (namely PMS and AUTOCAD), the authors investigated the learning curve using data on the volume of projects completed within the department and across the organisation as proxies for departmental and organisation experience, respectively. The authors found that there was a positive and significant relationship between organisational experience and productivity, and that information technology that aids the production process directly drives productivity improvement.

In a similar study, Plaza et al. (2010) proposed a model for quantifying the rate of learning and knowledge transfer in Enterprise Resource Planning (ERP) for new information technology projects implementation. The authors used the logistics and progress function (S curve) to model the knowledge absorption capacity that allows team members to accomplish a project within a fixed time. They found that when team members are at a high level of performance due to previous experience with the project or intensive training, both curves can be used to measure learning. However, the progress function was more appropriate to track team performance after the start-up effect has been observed.

In a cardiac surgery study where the volume of cardiac surgical procedure assigned to a surgeon increases due to exit of a retiring surgeon, Ramanarayanan (2011) found that performing an additional surgical procedure reduces the probability of patient mortality by 0.14%, indicating a strong learning-by-doing effect. Ralli et al. (2020) also used the learning curve to investigate cost reductions in the number of Caissons constructed using data disaggregated by project stages. Comparing results and forecasts from different learning models, the authors found that unit man hours significantly decreases as more Caissons are constructed, exemplifying the effect of experience gained at each construction stage.

3.6.2. Financial services (banks)

Studies on the learning curve of financial services or banks are very few. This is because unlike the manufacturing and other service industries, operationalising the experience term in banks is difficult. One reason is that outputs in the financial services industry are ill-defined and do not conform to the standard input-output variables often used in learning studies. Nevertheless, a couple of researchers have applied the theory of organisational learning to evaluate bank experience. In what follows, I review the related papers, including the empirical strategies used.

Barnett et al. (1994) examined the performance of Illinois banks in terms of the year to year changes in return on average assets (ROAA). The authors used a dynamic performance model that incorporated competition and takeover rate of banks in Illinois. The recursive performance models used were as follows:

$$\partial Y_j / \partial t = r(\sigma \lambda_j + \alpha N_j + \pi' X_j + \gamma' \varpi_j - Y_j) \quad (3.12)$$

$$r(t) = \exp(a' W) \quad (3.13)$$

$$\lambda = \left[\frac{\phi[\Phi^{-1}(1-F(t))]}{F(t)} \right] \quad (3.14)$$

Where Y_j refers to the observed performance distribution among a population of banks at a point in time. N_j is the number of competitors. X_j is a vector that describe the state of each bank j (size, age, and branch strategist). ϖ_j refers to each bank's history thought to contribute to its development. r is the selection or instantaneous transition rate for bank takeovers. λ is the hazard function. ϕ is standard normal density, and Φ is standard normal distribution.

The authors found that performance is negatively related to banks' rate of being taken over only in profitable banks, and that competition can reduce a bank ROAA by 0.08. They also found that performance was related to experience (the historical path followed) and the distinctive competencies of the banks studied.

Relatedly, a study of deliberate learning in the corporate acquisition of banks in the USA was undertaken by Zollo and Singh (2004). The authors defined performance as Return on Assets (ROA) of an acquiring bank relative to average ROA of banks in the same

geographical area as the acquiring bank. The authors argued that productivity could result from two sources of experience: knowledge codification and acquisition experience. Knowledge codification was operationalised as the sum of acquisition tools developed by the acquiring bank. Acquisition experience was operationalised by the number of previous acquisitions completed. The empirical model used can be expressed as follows:

$$\Delta ROA = (ROA_{i,t+3} - ROA_{c,t+3}) - (ROA_{i,t-1} - ROA_{c,t-1}) \quad (3.15)$$

$$\Delta ROA = \alpha_1.I - \alpha_2.R + \alpha_3.C + \alpha_4.E + \alpha_5.C \times I + \alpha_6.R \times g + \alpha_7.\Omega + \varepsilon \quad (3.16)^6$$

Where $ROA_{i,t+3}$ and $ROA_{i,t-1}$ are the return on assets of acquiring bank i in years $t+3$ and $t-1$, respectively. $ROA_{c,t+3}$ and $ROA_{c,t-1}$ are the average return on assets in the same geographic area of the acquiring bank c in years $t+3$ and $t-1$, respectively. They found that knowledge codification strongly and positively influences acquisition performance, but acquisition experience does not.

Kim et al. (2009) studied survival enhancing learning derived from a bank's own extreme performance experiences (success and recovery). The authors defined success experience (SE) 'as firms' (banks) cumulative history of exceptionally strong performance', and recovery experience (RE) as 'a type of failure experience that occurred when firms (banks) recovered from extremely poor performance'. Both experience terms were operationalised using CAMEL (Capital adequacy, Asset quality, Management, Earnings, Liquidity, and Sensitivity) ratings per discount factor. They argued that bank failure rate is a function of cumulative success and recovery experiences, in addition to organisational characteristics, industry and environmental conditions, operating experience, etc. Empirically, both experience terms were determined as follows:

$$SE = \sum_{j=t_c}^{t-1} SE_{ij} / \delta \quad (3.17)$$

$$RE = \sum_{j=t_c}^{t-1} RE_{ij} / \delta \quad (3.18)$$

Where δ is discount factor.

⁶ I - integration, R - replacement, C - codification, E - experience, g - quality, Ω - controls.

Using a piecewise exponential function to estimate bank failure, the authors showed that both success and failure experiences generate survival-enhancing learning in the banks only after a certain experience is reached.

More recently, Bush (2015) tested for the experience effect in banks' production using operating experience. The author specified a cost function that incorporates operating experience (years since the charter was granted). The empirical model can be expressed as follows:

$$C_i = e^{\alpha} \cdot Q_i^{\beta_q} \cdot \prod_g W_{g,i}^{\gamma_g} \cdot K_i^{\beta_k} \cdot R_i^{\beta_r} \cdot E_i^{\beta_f} \quad (3.19)$$

Where C is the total cost of bank i , Q represents the earning assets of bank i , W represents input prices, K is equity capital, R is asset quality (non-performing loan), and E is bank operating experience (measured in years since the charter was granted). The author provides evidence of cost reduction through learning in the banking sector by showing that cost reduces by 10.9 percent with a 10 percent gain in the experience of a bank at approximately 1 year of age.

From the literature review, not much has been done in applying the learning curve to the financial services industry, and to banks, in particular. One of the major undertakings of this thesis is to contribute to the few bodies of literature that have measured bank experience using various concept as reviewed above. The next chapter develops a framework to apply the learning curve to banks.

Table 3.1 summarises a few learning studies, the industries studied, and how knowledge (experience) was operationalised.

Table 3.1. Summary of some learning curve studies and the experience terms used*

S/No	Author(s)	Experience term (output)	Industry	Sub-industry
1	Bahk and Gort (1993)	Shipment value/value added	Manufacturing	15 sub-industries
2	Barnett et al. (1994)	Takeover rate	Financial services	Banks
3	Darr et al. (1995)	Volume of pizzas	Service	Fast food chains
4	Baum and Ingram (1998)	Volume of available rooms	Service	Hotel industry
5	Pramongkit et al. (2000)	Value added	Manufacturing	Several
6	Lapre and Van Wassenhove (2001)	TFP	Manufacturing	Steel wire factory
7	Boone and Ganeshan (2001)	Volume of project completed	Service	Information technology
8	Pramongkit et al. (2002)	Value added	Manufacturing	Several
9	Zollo and Singh, (2004)	Sum of acquisition tools and volume of acquisitions	Financial services	Banks
10	Karaoz and Albeni (2005)	Value added	Manufacturing	Several
11	Asgari and Yen (2009)	Value added	Manufacturing and service	Several
12	Kim et al. (2009)	CAMELS rating	Financial services	Banks
13	Plaza et al. (2010)	Man hours/project duration	Service	Information technology
14	Ramanarayanan (2011)	Volume of cardiac operation	Service	Hospital
15	Levitt et al. (2013)	Volume of cars produced	Manufacturing	Automobile
16	Bush (2015)	Operating experience (years)	Financial services	Banks
17	Egelman et al. (2017)	Volume of shipment	Manufacturing	Technology hardware
18	Aduba and Asgari (2020)	Value added	Manufacturing	Several
19	Ralli et al. (2020)	Volume of Caissons constructed	Service	Construction

*This list is by no means exhaustive.

Appendix 3A

Learning Incorporated in Production Function

I. The log-linear case.

The most general form of the learning curve is expressed as follows:

$$\tau_t = \theta \cdot X_t^{-\phi} \rightarrow \ln \tau_t = \theta - \phi \ln X_t + e_t \quad (3A.1)$$

Suppose that the general form of a Cobb-Douglas production could be expressed as follows:

$$Q_t = \Delta_t \cdot L_t^\alpha \cdot K_t^\beta \rightarrow \ln Q_t = \ln \Delta_t + \alpha \ln L_t + \beta \ln K_t \quad (3A.2)$$

Δ_t depicts the current level of technology or advances in knowledge at time t . Δ_t is assumed to be proportional to the accumulated experience (cumulative output) and can be represented as follows:

$$\Delta_t = \varphi X_t^\phi \rightarrow \ln \Delta_t = \ln \varphi + \phi \ln X_t \quad (3A.3)$$

φ is proportionality constant, and X_t^ϕ is the inverse of $X_t^{-\phi}$ in (3A.1). Further, the following holds for Δ_t .

$$\Delta_t = \varphi \frac{\theta}{\tau_t} \rightarrow \ln \Delta_t = \ln \varphi + \ln \left(\frac{\theta}{\tau_t} \right) \quad (3A.4)$$

Following (3A.3), a new production function can be established as follows:

$$\ln Q_t = \ln \varphi + \phi \ln X_t + \alpha \ln L_t + \beta \ln K_t \quad (3A.5)$$

By further derivation, we have equation (3A.6).

$$\ln \left(\frac{L}{Q} \right)_t = -\ln \varphi - \phi \ln X_t + (1 - \alpha) \ln L_t - \beta \ln K_t \quad (3A.6)$$

As output expands, the relationship between labour and capital can be expressed as follows⁷.

$$K_t = \mu L_t^\lambda \rightarrow \ln K_t = \ln \mu + \lambda \ln L_t \quad (3A.7)$$

⁷ The value of λ indicates the technical biases associated with production expansion. $\lambda=1$ indicates neutrality in technological progress, whereas $\lambda>1$ suggests that the capital labour ratio proportionately increases as output expands (Pramongkit et al., 2000; Karaoz & Albeni, 2005)

Replacing the new value of $\ln K_t$ in equation (3A.6) gives the final log-linear empirical estimation equation for the learning curve as follows:

$$\ln\left(\frac{L}{Q}\right)_t = -\ln\varphi - \beta\ln\mu - \phi\ln X_t + (1 - \alpha - \beta\lambda)\ln L_t \quad (3A.8)$$

More conveniently, it can be expressed as follows:

$$\ln Y_t = \omega + \vartheta\ln L_t + \phi\ln X_t + \varepsilon_t \quad (3A.9)$$

Where $\ln C_t = \ln\left(\frac{L}{Q}\right)_t$, $\omega = -\ln H - \gamma\ln\mu$, $\vartheta = 1 - \beta - \gamma\lambda$, and $\phi = -\phi$. ε_t is the stochastic term, and μ and λ are constants.

II. The cubic approximation of the learning curve.

It is possible to approximate the learning curve with a cubic function which allows both disaggregation and forecasting of the learning rates. The cubic functional form can be expressed as follows:

$$\ln\tau_t = \ln\theta + \phi_1\ln X_t + \phi_2(\ln X_t)^2 + \phi_3(\ln X_t)^3 \quad (3A.10)$$

Expressing equation (3A.10) in terms of the ratio between a unit cost of producing the first unit (θ) and the unit production cost in time t (τ_t) produces the following:

$$\ln\left(\frac{\theta}{\tau_t}\right) = -(\phi_1\ln X_t + \phi_2(\ln X_t)^2 + \phi_3(\ln X_t)^3) \quad (3A.11)$$

As noted in equation (3A.4), a new expression in terms of Δ_t emerges from equation (3A.11) as follows:

$$\ln\Delta_t = \ln\varphi - \phi_1\ln X_t - \phi_2(\ln X_t)^2 - \phi_3(\ln X_t)^3 \quad (3A.12)$$

Substituting for $\ln\Delta_t$ in equation (3A.2) and following similar derivation as above, the following are established:

$$\ln Q_t = \ln\varphi - \phi_1\ln X_t - \phi_2(\ln X_t)^2 - \phi_3(\ln X_t)^3 + \alpha\ln L_t + \beta\ln K_t \quad (3A.13)$$

$$\ln Q_t = \ln\varphi - \phi_1\ln X_t - \phi_2(\ln X_t)^2 - \phi_3(\ln X_t)^3 + \alpha\ln L_t + \beta(\ln\mu + \lambda\ln L_t) \quad (3A.14)$$

$$\ln\left(\frac{L}{Q}\right)_t = -\ln\varphi - \beta\ln\mu + \phi_1\ln X_t + \phi_2(\ln X_t)^2 + \phi_3(\ln X_t)^3 + (1 - \alpha - \lambda)\ln L_t \quad (3A.15)$$

Or conveniently as,

$$\ln Y_t = \omega + \vartheta \ln L_t + \phi_1 \ln X_t + \phi_2 (\ln X_t)^2 + \phi_3 (\ln X_t)^3 + e_t \quad (3A.16)$$

Where $\omega = -\ln H - \gamma \ln \mu$, $\vartheta = (1 - \beta - \lambda)$, and $\ln Y_t = \ln \left(\frac{L}{Q} \right)_t$.

The first derivative of equation (3A.10) with respect to $\ln X_t$ gives the learning elasticity for the cubic approximation, which can be expressed as,

$$\partial \ln C_t / \partial \ln X_t = \phi_1 + 2. \phi_2 \ln X_t + 3. \phi_3 (\ln X_t)^2 \quad (3A.17)$$

Chapter 4

Conceptual Framework and Research Method

4.1. Introduction

The literature review on organisational learning in banks shows that a couple of authors who have measured bank experience used different empirical specifications. For example, Bush (2015) used a cost function that incorporates a bank's years of operation as a measure of bank experience. I argue that while years of operation could serve as a proxy for the experience term in applying the learning curve to banks, other variables may also capture the learning behaviours in bank production and financial intermediation activities. Moreover, Bush (2015) showed that experience fades around 10 years of age, that is, older banks (measured by longer years in operation) do not necessarily demonstrate cost-efficiency gain. Hence, further investigation with other proxies of experience is a good research agenda. Here, I formulate an empirical model that incorporates learning. I also define outputs in banks that capture bank experience in *credit* and *value creation*. The former relies upon bank investment streams, namely loan production, security investment, and other earning assets. The latter involve estimating *economic value added* (shareholder value) and *gross value-added (FISIM)*⁸. I argue that the learning characteristics of banks can be modelled if bank experience in credit and value creation are correctly operationalised.

4.2. Research methods

I assume a bank production technology with three inputs (physical capital ψ , deposits and other borrowed fund D , and financial capital or equity K) that follows a Cobb-Douglass production function expressed as follows:

$$\emptyset = \beta_0 \psi^{\beta_1} \cdot D^{\beta_2} \cdot K^{\beta_3} \quad (4.1)$$

The total bank cost of producing output \emptyset is expressed as follows:

$$\mathcal{C} = w_p \psi + w_d D + w_k K \quad (4.2)$$

⁸ FISIM stands for Financial Intermediation Services Indirectly Measured.

If $\mathcal{Q} = f(\emptyset)$, then the constrained output maximisation is expressed as follows:

Maximise

$$\emptyset = \beta_0 \psi^{\beta_1} \cdot D^{\beta_2} \cdot K^{\beta_3} \quad (4.3)$$

s.t.

$$\hat{\mathcal{Q}} = w_p \psi + w_d D + w_k K \quad (4.4)$$

The composite function of the constrained equation becomes the following:

$$\xi = \emptyset + \eta(\hat{\mathcal{Q}} - w_p \psi - w_d D - w_k K) \quad (4.5)$$

Where η is the lagrangian multiplier.

The first-order condition ensures that the first derivative of equation (4.5) with respect to ψ, D, K , and η equal to zero.

$$\frac{\partial \xi}{\partial \psi} = \beta_1 \frac{\emptyset}{\psi} - \eta w_p = 0 \quad (4.6)$$

$$\frac{\partial \xi}{\partial D} = \beta_2 \frac{\emptyset}{D} - \eta w_d = 0 \quad (4.7)$$

$$\frac{\partial \xi}{\partial K} = \beta_3 \frac{\emptyset}{K} - \eta w_k = 0 \quad (4.8)$$

$$\frac{\partial \xi}{\partial \eta} = (\hat{\mathcal{Q}} - w_p \psi - w_d D - w_k K) = 0 \quad (4.9)$$

Combining equations (4.6) and (4.7), expressed in terms of D, yields the following:

$$D = \left(\frac{w_p \beta_2}{w_d \beta_1} \right) \psi \quad (4.10)$$

Solving for D in equation (4.3) yields the following:

$$\emptyset = \beta_0 \psi^{\beta_1} \cdot \left(\frac{w_p \beta_2}{w_d \beta_1} \psi \right)^{\beta_2} \cdot K^{\beta_3} \rightarrow \emptyset = \beta_0 \left(\frac{w_p \beta_2}{w_d \beta_1} \right)^{\beta_2} \psi^{\beta_1 + \beta_2} \cdot K^{\beta_3} \quad (4.11)$$

Similarly, combining equations (4.6) and (4.8), and deriving K yields the following:

$$K = \frac{w_p \beta_3}{w_k \beta_1} \psi \quad (4.12)$$

Substituting equation (4.12) in equation (4.11) yields the following:

$$\emptyset = \beta_0 \psi^{\beta_1} \left(\frac{w_p \beta_2}{w_d \beta_1} \psi \right)^{\beta_2} \cdot \left(\frac{w_p \beta_3}{w_k \beta_1} \psi \right)^{\beta_3} \rightarrow \emptyset = \beta_0 \left(\frac{w_p \beta_2}{w_d \beta_1} \right)^{\beta_2} \cdot \left(\frac{w_p \beta_3}{w_k \beta_1} \right)^{\beta_3} \psi^{\beta_1 + \beta_2 + \beta_3} \quad (4.13)$$

Expressing (4.13) in terms of ψ yields the following:

$$\psi = \left[\frac{1}{\left(\frac{w_p \beta_2}{w_d \beta_1}\right)^{\beta_2} \left(\frac{w_p \beta_3}{w_k \beta_1}\right)^{\beta_3}} \cdot \left(\frac{\emptyset}{\beta_0}\right) \right]^{\frac{1}{(\beta_1 + \beta_2 + \beta_3)}} \quad (4.14)$$

$$\psi = \left(\frac{w_d \beta_1}{w_p \beta_2}\right)^{\frac{\beta_2}{(\beta_1 + \beta_2 + \beta_3)}} \cdot \left(\frac{w_k \beta_1}{w_p \beta_3}\right)^{\frac{\beta_3}{(\beta_1 + \beta_2 + \beta_3)}} \cdot \left(\frac{\emptyset}{\beta_0}\right)^{\frac{1}{(\beta_1 + \beta_2 + \beta_3)}} \quad (4.15)$$

Substituting equation (4.15) into equation (4.10) yields the following:

$$D = \left(\frac{w_p \beta_2}{w_d \beta_1}\right) \left\{ \left(\frac{w_d \beta_1}{w_p \beta_2}\right)^{\frac{\beta_2}{(\beta_1 + \beta_2 + \beta_3)}} \cdot \left(\frac{w_k \beta_1}{w_p \beta_3}\right)^{\frac{\beta_3}{(\beta_1 + \beta_2 + \beta_3)}} \cdot \left(\frac{\emptyset}{\beta_0}\right)^{\frac{1}{(\beta_1 + \beta_2 + \beta_3)}} \right\} \quad (4.16)$$

$$D = \left(\frac{w_p \beta_2}{w_d \beta_1}\right)^{\frac{(\beta_1 + \beta_3)}{(\beta_1 + \beta_2 + \beta_3)}} \cdot \left(\frac{w_p \beta_3}{w_k \beta_1}\right)^{\frac{\beta_3}{(\beta_1 + \beta_2 + \beta_3)}} \cdot \left(\frac{\emptyset}{\beta_0}\right)^{\frac{1}{(\beta_1 + \beta_2 + \beta_3)}} \quad (4.17)$$

Furthermore, recall that $K = \left(\frac{w_p \beta_3}{w_k \beta_1}\right) \cdot \psi$. Again, substituting from equation (4.15) yields the following:

$$K = \left(\frac{w_p \beta_3}{w_k \beta_1}\right) \left\{ \left(\frac{w_d \beta_1}{w_p \beta_2}\right)^{\frac{\beta_2}{(\beta_1 + \beta_2 + \beta_3)}} \cdot \left(\frac{w_k \beta_1}{w_p \beta_3}\right)^{\frac{\beta_3}{(\beta_1 + \beta_2 + \beta_3)}} \cdot \left(\frac{\emptyset}{\beta_0}\right)^{\frac{1}{(\beta_1 + \beta_2 + \beta_3)}} \right\} \quad (4.18)$$

$$K = \left(\frac{w_d \beta_1}{w_p \beta_2}\right)^{\frac{\beta_2}{(\beta_1 + \beta_2 + \beta_3)}} \cdot \left(\frac{w_p \beta_3}{w_k \beta_1}\right)^{\frac{(\beta_1 + \beta_2)}{(\beta_1 + \beta_2 + \beta_3)}} \cdot \left(\frac{\emptyset}{\beta_0}\right)^{\frac{1}{(\beta_1 + \beta_2 + \beta_3)}} \quad (4.19)$$

Therefore, the total bank cost function in equation (4.2) expressed in terms of input prices w_p, w_d, w_k , and output \emptyset as follows:

$$\begin{aligned} \mathcal{C} = & \left(\frac{1}{\beta_0}\right)^{\frac{1}{(\beta_1 + \beta_2 + \beta_3)}} \left\{ w_p \left[\left(\frac{w_d \beta_1}{w_p \beta_2}\right)^{\frac{\beta_2}{(\beta_1 + \beta_2 + \beta_3)}} \cdot \left(\frac{w_k \beta_1}{w_p \beta_3}\right)^{\frac{\beta_3}{(\beta_1 + \beta_2 + \beta_3)}} \right] + \right. \\ & w_d \left[\left(\frac{w_p \beta_2}{w_d \beta_1}\right)^{\frac{(\beta_1 + \beta_3)}{(\beta_1 + \beta_2 + \beta_3)}} \cdot \left(\frac{w_p \beta_3}{w_k \beta_1}\right)^{\frac{\beta_3}{(\beta_1 + \beta_2 + \beta_3)}} \right] + \\ & \left. w_k \left[\left(\frac{w_d \beta_1}{w_p \beta_2}\right)^{\frac{\beta_2}{(\beta_1 + \beta_2 + \beta_3)}} \cdot \left(\frac{w_p \beta_3}{w_k \beta_1}\right)^{\frac{(\beta_1 + \beta_2)}{(\beta_1 + \beta_2 + \beta_3)}} \right] \right\} \cdot \emptyset^{\frac{1}{(\beta_1 + \beta_2 + \beta_3)}} \quad (4.20) \end{aligned}$$

From the foregoing, the final bank total cost function expressed in terms of input prices w_p, w_d, w_k , and the output \emptyset is expressed as follows:

$$\mathcal{C} = e^{\omega} \cdot \left\{ w_p^{\frac{\beta_1}{(\beta_1 + \beta_2 + \beta_3)}} \cdot w_d^{\frac{\beta_2}{(\beta_1 + \beta_2 + \beta_3)}} \cdot w_k^{\frac{\beta_3}{(\beta_1 + \beta_2 + \beta_3)}} \right\} \cdot \emptyset^{\frac{1}{(\beta_1 + \beta_2 + \beta_3)}} \quad (4.21)$$

Where $e^\omega = \left\{ \left(\frac{1}{\beta_0} \right) \left[\left(\frac{\beta_1}{\beta_2} \right)^{\beta_2} \left(\frac{\beta_1}{\beta_3} \right)^{\beta_3} + \left(\frac{\beta_2}{\beta_1} \right)^{\beta_1 + \beta_3} \left(\frac{\beta_3}{\beta_1} \right)^{\beta_3} + \left(\frac{\beta_1}{\beta_2} \right)^{\beta_2} \left(\frac{\beta_3}{\beta_1} \right)^{\beta_1 + \beta_2} \right] \right\}^{\frac{1}{(\beta_1 + \beta_2 + \beta_3)}}$.

For convenience, from equation (4.21), the final total cost function for bank i at time t , with bank-specific production technology adjusted for asset quality (risk) R can be expressed as follows:⁹

$$\mathcal{C}_{t,i} = e^\omega \cdot \phi_{t,i}^{\beta_\phi} \cdot \prod_s w_{s,t,i}^{\beta_s} \cdot R_{t,i}^{\beta_r} \quad (4.22)$$

Taking the log of equation (4.22) yields the empirical estimation form as follows:

$$\ln \mathcal{C}_{t,i} = \omega + \beta_\phi \ln \phi_{t,i} + \sum_s (\beta_s) \ln w_{s,t,i} + \beta_r \ln R_{t,i} + \varepsilon_{t,i} \quad (4.23)$$

Where R_i is asset quality proxied by the level of non-performing loans. Non-performing loan, in recent times, have become an important quasi-fixed input in modelling bank production and useful as a control variable for risky behaviours in banks (Hughes & Mester, 2014; Radić, 2015). ε_i is the stochastic term.

From equation (4.23), a cost function that incorporates experience or learning can be specified as follows:

$$\ln \mathcal{C}_{t,i} = \omega + \beta_\phi \ln \widehat{\phi}_{t-1,i} + \sum_s \beta_s \ln w_{s,t,i} + \beta_r \ln R_{t,i} + \varepsilon_{t,i} \quad (4.24)$$

Where $\widehat{\phi}_{t-1,i}$ is the lagged cumulative output produced through time t , proxied for experience gained with bank production or financial intermediation services. Under this specification, learning is measured by the significant positive coefficient of the experience term (β_ϕ).

Furthermore, following empirical literature on the learning curve, I hypothesise that *unit cost decreases with cumulative output* (Aduba & Asgari, 2020; Darr et al., 1995; Karaoz & Albeni, 2005; Levitt et al., 2013). Therefore, I express equation (4.24) in terms of unit cost as follows:

$$\ln \Gamma_{t,i} = \omega + \beta_\phi \ln \widehat{\phi}_{t-1,i} + \sum_s \beta_s \ln w_{s,t,i} + \beta_r \ln R_{t,i} + \varepsilon_{t,i} \quad (4.25)$$

⁹ The alternative to equation (4.26) will be to treat equity capital as quasi-fixed input and minimize cost condition on the level of equity K . In this case, equation (4.26) will include equity level K , but exclude cost of equity. However, using trans-log cost function equation (4.33), I estimated the shadow price of equity w_k using equation (4.34). Hence, I treated equation (4.26) as a full economic cost function with observable factor prices.

Where $\Gamma_{t,i} = \left(\frac{c_{t,i}}{\phi_{t,i}}\right)$ is the cost required to produce an additional unit of output. The coefficient β_ϕ is crucial and indicates whether learning has occurred. A significant negative β_ϕ in equation (4.25) implies that learning has occurred, that is, unit cost decreases as experience is gained¹⁰.

As demonstrated in the literature review in Chapter 3, it is possible to approximate equation (4.25) by a cubic function to allow for dynamic estimation of annual learning rates¹¹. This can be expressed as follows:

$$\ln \Gamma_{t,i} = \omega + \beta_{\phi 1} \ln(\hat{\phi}_{t-1,i}) + \beta_{\phi 2} \ln(\hat{\phi}_{t-1,i})^2 + \beta_{\phi 3} \ln(\hat{\phi}_{t-1,i})^3 + \sum_s (\beta_s) \ln w_{s,t,i} + \beta_r \ln R_{t,i} + \varepsilon_{t,i} \quad (4.26)$$

The first derivative of equation (4.26) with respect to $\ln \hat{\phi}_{t-1,i}$ gives the learning elasticity ($\Omega_{t,i}$) expressed as follows:

$$\Omega_{t,i} = \frac{\partial(\ln \Gamma_{t,i})}{\partial \ln \hat{\phi}_{t-1,i}} = \beta_{\phi 1} + 2 \cdot \beta_{\phi 2} \ln \hat{\phi}_{t-1,i} + 3 \cdot (\beta_{\phi 3} \ln \hat{\phi}_{t-1,i})^2 \quad (4.27)$$

Equation (4.27) enables us to disentangle annual learning rates (progress ratio δ_t) of bank i at time t . The progress ratio in equation (4.28) enables us to see whether learning is progressive or lost during the period under consideration¹².

$$\delta_{t,i} = 2^{\Omega_{t-1,i}} \quad (4.28)$$

For a progressive learning bank, δ_t lies between 0 and less than 1 ($0 < \delta_t < 1$). All $\delta_{t,i} \geq 1$ implies that learning is lost, or no learning has occurred in the domain of the output proxied for the cumulative experience. This simply means that unit cost decreases as output accumulates.

This framework is used to study the learning curve of a sample of Nigerian commercial banks in Chapter 5.

¹⁰ The two specifications of the learning curve model differ only in the dependent variable and the theoretical expected coefficient of experience term.

¹¹ The cubic learning function is especially important for estimating the dynamic annual learning rates (Badiru, 1992; Karaoz & Albeni, 2005; Aduba & Asgari, 2020).

¹² The general form of the progress ratio is expressed as, $\delta = 2^\gamma$, where γ is the coefficient of the experience term.

4.3. Outputs: Defining and measuring experience in bank production

In addition to developing the appropriate framework to study the learning curve in banks, the other task is defining appropriate outputs in banks that can adequately capture bank experience in production. This is because outputs in banks depend on the study's approach and the bank production technologies adopted. Defining production technologies in banks begins with operationalising the role of banks. Bank operations generally cover three important elements: profit maximisation (risk management), service provision (intermediation and utility provision), and value addition (Berger and Humphrey, 1992; Grigorian and Manole, 2006; Drake et al., 2006). To study the learning curve of banks, I combine these three elements, and define bank inputs and outputs according to the value-added and intermediation approach. Yet, not all outputs according to these two definitions qualify as experience terms.

Experience terms are usually operationalised in terms of widgets of outputs and their cumulative values in learning curve studies. In the case of banks, this is problematic because outputs (the charge for services) are somewhat difficult to measure. To overcome this difficulty, I identify bank outputs that improve when banks acquired knowledge by producing these specific outputs¹³. I redefine banks' roles in two broad ways: *value creation* and *credit creation* (investment or risk management). Figure 4.1 is a concept that enables us to better understand and define bank experience terms.

¹³ The list of outputs considered here is by no means exhaustive.

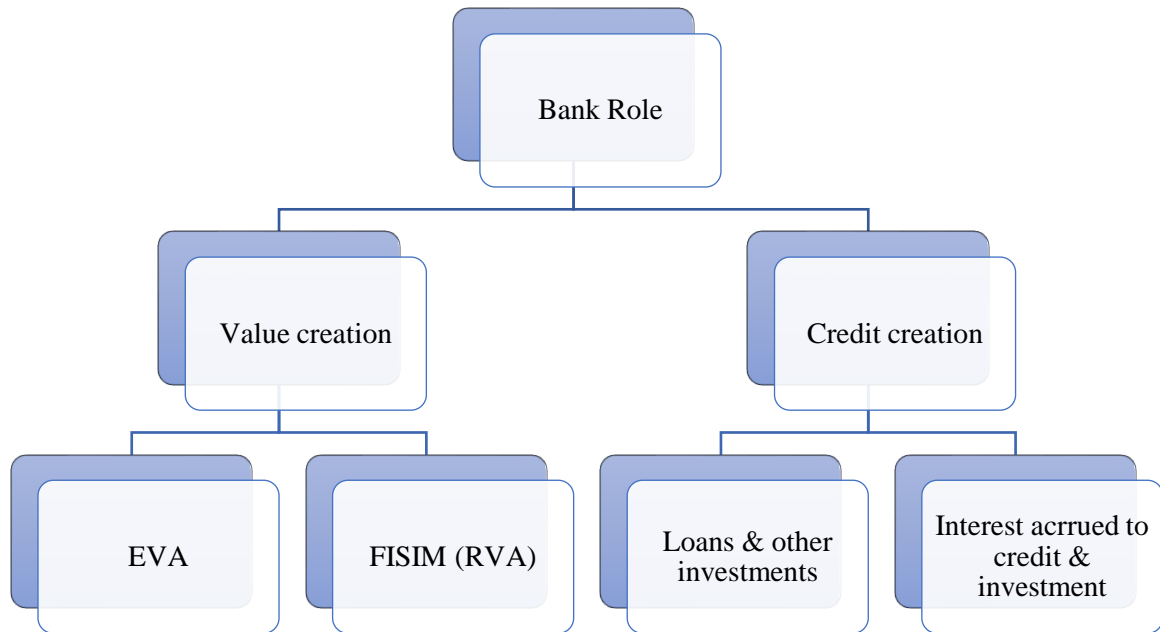


Figure 4.1. Conceptual framework (Source: author).

4.3.1. Value Creation

To measure the learning curve of banks in the domain of value creation, I identify two outputs that could proxy for experience in banks: Economic Value Added (EVA, \emptyset_{eva})¹⁴ and FISIM (\emptyset_{fisim})¹⁵. Compared with the empirical literature on the learning curve, these widgets of outputs can be cumulated over time since they are uniquely defined for each business cycle (fiscal year). Next, I describe the framework for measuring the two identified proxies of value creation in banks.

4.3.1.1. Economic value-added (EVATM): Definition and estimation

EVA is the surplus generated by a firm after meeting equitable charge for providers of capital. In the banking sector, EVA is defined as the difference between the economic measure of a bank's net operating profit and the capital charge over the same period

¹⁵ FISIM (Financial Intermediation Services Indirect Measure) is the bank output derived from the spread between loan interest receipts and deposit interest payments.

(Fiordelisi & Molyneux, 2010). The EVA framework pummels managers to charge for the use of the capital invested, first as a recognition of their obligation to create value for the shareholders, and second as a reward (compensation) for the riskiness of shareholders equity investment (Uyemura et al., 1996). The EVA framework is rooted in the theory of economic profit in that it recognises and adjusts earning based on the opportunity cost of capital. Hence, I argue that EVA is synonymous to ‘true economic profit’ and can be defined as ‘*the extent that earnings exceed the returns that could be earned from other investment opportunities*’ (Kimball, 1998). This description shows that EVA can provide a good measure of bank experience in value creation, and therefore, qualifies to be used as experience term.

In applying the EVA framework to banks, some adjustments are needed to convert accounting statements to economic statements (Fiordelisi, 2007; Fiordelisi & Molyneux, 2010; Radić, 2015)¹⁶. For example, loan loss provision, in theory, provides for future monitoring of loan loss exposure according to management best practises. In practical terms, however, this practice is opportunistic and often distorts earnings in a manner that is counterproductive to economic performance measurement. Moreover, under this practice, risk is being treated as subjective and anticipatory instead of being done on a real-time basis as volatility in economic profits. Hence, treating this item as present earning corrects this bias. In a similar vein, items such as provisions for future tax, non-recurrent expense, and securities are adjusted and spread over the accounting period to correct for biases to the current value of net earnings.

To estimate EVA, I follow empirical bank studies and define EVA ($\varphi_{t,i}$) as the economic measure of a bank’s net operating profit adjusted for tax ($\omega_{t,i}$) less capital charge. Capital charge is defined as the product of capital employed (ϵ_t) and the estimated cost of capital ($w_{t,i}$).

$$\varphi_{t,i} = \omega_{t,i} - w_{t,i} \cdot \epsilon_t \quad (4.29)$$

Next, I calculated ($\omega_{t,i}$) and (ϵ_t) by accounting for bank-specific features. To calculate the cost of capital $w_{t,i}$, I adopt the method proposed by Hughes et al. (2001), Fiordelisi

¹⁶ I adjust for loan loss provision, tax provision, other provisions, non-recurrent events, and security accounting.

and Molyneux (2010), and Radić (2015). I include the level of equity as a quasi-fixed input in the trans-log cost function (equation (4.30)). These authors showed that the shadow price of equity provides a good measure of the opportunity cost of capital. The price of capital ($w_{t,i}$) is thus calculated by taking the negative derivative of a standard trans-log bank cost function (4.30)¹⁷ with respect to equity capital (E_k) to get price of capital (w_k) as expressed in equation (4.31) below.

$$\begin{aligned} \ln\left(\frac{C_i}{\gamma_3}\right) = & \theta_0 + \sum_i \theta_i \ln \phi_i + \beta_{\gamma_1} \ln\left(\frac{\gamma_1}{\gamma_3}\right) + \beta_{\gamma_2} \ln\left(\frac{\gamma_2}{\gamma_3}\right) + \tau \ln E_k + t_1 T + \frac{1}{2} \left[\sum_i \sum_j \theta_{ij} \ln \phi_i \ln \phi_j + \right. \\ & \beta_{\gamma_{11}} \ln\left(\frac{\gamma_1}{\gamma_3}\right) \ln\left(\frac{\gamma_1}{\gamma_3}\right) + \beta_{\gamma_{22}} \ln\left(\frac{\gamma_2}{\gamma_3}\right) \ln\left(\frac{\gamma_2}{\gamma_3}\right) + \sigma \ln E_k \ln E_k + t_{11} T^2 \left. \right] + \beta_{\gamma_{12}} \ln\left(\frac{\gamma_1}{\gamma_3}\right) \ln\left(\frac{\gamma_2}{\gamma_3}\right) + \\ & \sum_i \theta_{i\gamma_1} \ln \phi_i \ln\left(\frac{\gamma_1}{\gamma_3}\right) + \sum_i \theta_{i\gamma_2} \ln \phi_i \ln\left(\frac{\gamma_2}{\gamma_3}\right) + \sum_i \theta_{ik} \ln \phi_i \ln E_k + \sum_i \theta_{it} T \ln \phi_i \ln E_k + \\ & \beta_{\gamma_{1k}} \ln\left(\frac{\gamma_1}{\gamma_3}\right) \ln E_k + \beta_{\gamma_{2k}} \ln\left(\frac{\gamma_2}{\gamma_3}\right) \ln E_k + \beta_{\gamma_{1t}} T \ln\left(\frac{\gamma_1}{\gamma_3}\right) + \beta_{\gamma_{2t}} T \ln\left(\frac{\gamma_2}{\gamma_3}\right) + \varepsilon_t \end{aligned}$$

(4.30) Where $\sum_j \beta_{\gamma_j} = 1$, $\sum_j \beta_{\gamma_{jr}} = 0 \forall r$, and $\sum_j \theta_{i\gamma_j} = 0$.

$$w_k = - \left(\frac{\partial \ln C_{it}}{\partial \ln \epsilon_k} \right) \quad (4.31)$$

Where C_i is the total cost of bank i , ϕ_i is the vector of outputs for bank i , γ_i ($i = 1, 2, 3$) is a vector of bank input prices, E_k is the level of equity capital, and T is the time trend. The output is a vector of four variables: loans and advances, ϕ_1 , security investment (ϕ_2), liquid cash (ϕ_3), and other interest-bearing assets (ϕ_4). Input prices are computed as interest expense over debt (γ_1), cost of labour over the total number of employees (γ_2), and non-interest expense over fixed assets (γ_3). I define equity capital E_k as the sum of shareholder equity, provision for loans loss reserve, and other reserves.

4.3.1.2. Financial Intermediation Services Indirect Measure (FISIM)

FISIM is the new framework for calculating financial institutions output (especially in banks) according to SNA 2008. FISIM is an update to the IBSC, which involves methodological change that recognises some element of a bank's role, such as risk assessment in deposits and loans/security investment that yield gross interest output¹⁸.

¹⁷ I impose homogeneity constraints in factor inputs by normalizing total cost and the other input prices by the third input price (γ_3), and exclude the third from the model.

¹⁸ SNA and IBSC stand for System of National Accounts and Imputed Bank Service Charge.

This approach was found to enhance the computation of the gross value added in financial institutions, compared to the IBSC which ignores adjustment in risk components.

FISIM can be estimated as follows:

$$FISIM = FISIM_L + FISIM_D \quad (4.32)$$

$$FISIM = (r_l - r_r) * G_L + (r_r - r_d) * G_D \quad (4.33)$$

Where r_l is the loan interest rate, r_d is the deposit interest rate, r_r is a reference rate, G_L represents total loans, and G_D represents total deposits.

The reference rate r_r is taken as the interbank interest rate. The loan interest rate refers to the ratio of loan interest to total loan. The deposit interest rate is the ratio of interest paid on loanable fund divided by the total deposit. The FISIM framework treats banks as financial intermediaries whose sole productive activity is connecting borrowers to lenders. From the view of defining the experience term in banking, I consider FISIM appropriate because it involves some measure of learning to manage financial risks that enables it to gauge the appropriate spread between interest received and interest paid out to earn a positive compensation.

4.3.2. Credit creation

The second approach to evaluating learning in banks is through credit creation. Banks create credit by raising capital either through their own funds or through debt financing. To measure bank experience through credit creation, I proceed as follows:

First, I define \emptyset_{TC} as the sum of all credits created or ‘earning assets’ (loans, security, and other interest-bearing investment) as a proxy to investigate learning by investment or risk-taking. I posit that credit creation involves intensive information gathering and adequate knowledge about applicant population, risk dynamics, and adequate knowledge about the interest spread that could yield positive returns. In banks, \emptyset_{TC} cannot be cumulated because it occurs naturally as a cumulative value less repairment and reported as the consolidated amount for each fiscal year. Understandably, \emptyset_{TC} fluctuates and might be affected by management objectives and bank risk dynamics. Nevertheless, productive banks, in general, will make an attempt to ensure steady growth in \emptyset_{TC} as much as possible.

$$\Phi_{TC} = \sum_j TC \quad (4.34)$$

Where TC is Total Credit and represents the sum of all j interest-bearing investments.

An alternative to Φ_{TC} is the total interest accrued to a bank, generally reported as interest income Φ_{TI} . As a widget of output reported for each fiscal year, Φ_{TI} can be cumulated. It can provide a good measure of efficiency in credit creation. Φ_{TI} is estimated as follows:

$$\Phi_{TI} = \sum_{i=i} TI \quad (4.35)$$

Where TI is cumulative interest income.

In Nigeria, deposits constitute a significant source of bank financing. Therefore, the management's drive to raise capital to finance bank assets (create credit) involves some level of learning in the domain of deposit-taking. These may include deliberate actions or strategies such as promotions that incentivise customers to increase deposit amount or a drive for new customers. This learning phenomenon will undoubtedly manifest itself in credit creation.

In summary, evaluating bank experience through a credit creation approach might provide insights into managerial objectives and investment drive in the banking industry.

4.4. Inputs

There are three main bank inputs considered in this study viz. physical capital (labour and value of physical assets), deposits (including all other borrowed funds), and equity capital. What constitutes inputs in bank studies also depends on the definition of bank production technology adopted. Nevertheless, inputs in banks have been well defined when intermediation or value-added approaches are implemented. Furthermore, identifying inputs becomes even easier based on the previously described credit and value creation roles of banks.

Researchers have argued that deposits could be considered as an output. However, Hughes et al. (2001) empirically showed that the technological roles of deposits are consistent with that of input. In addition, new bank studies have increasingly recognised the role of equity capital as input due to its ability to substitute for debt in bank financing.

Following this logic, I estimate the price of equity capital and include it as input price of capital. Furthermore, like many bank studies, I include the level of non-performing loans as asset quality to penalise banks for underestimation of risky behaviour. I summarise all outputs and inputs variables in Table 4.1.

4.5. Hypothesis testing

The following hypothesis on the experience terms developed above are specified here. The decision rule of all hypotheses is based on column 6 of Table 4.1.

Hypothesis 1a. Unit cost decreases with cumulative experience in credit creation (loans).

Hypothesis 1b. Unit cost decreases with cumulative experience in credit creation (interest income).

Hypothesis 2. Unit cost decreases with cumulative experience in gross value added (lending to the real sector and service provision).

Hypothesis 3. Unit cost decreases with cumulative experience in economic value created.

Table 4.1. Variable descriptions and hypotheses.

Panel A: Outputs						
Output	Symbol	Description	Remarks	Expected sign of coefficient Hypothesis		
				Equation 4.24	Equation 4.25	
EVA	\emptyset_{eva}	Economic value-added, defined as a dollar surplus on capital invested.	Can be cumulated and proxied for experience shareholder in value creation.	Positive (+) and significant	Negative (-) and significant	Unit cost decreases with cumulative experience in economic value created.
FISIM	\emptyset_{fisim}	Spread between interest received and interest paid adjusted by a risk factor.	Can be cumulated and proxied for experience in credit/risk management.	Positive (+) and significant	Negative (-) and significant	Unit cost decreases with cumulative experience in gross value added to the economy.
TC	\emptyset_{TC}	Total credit created (sum of loans, security, liquid asset, and other interest-bearing assets).	Reported as cumulative issue and can be proxied for experience in total credit creation (interest-bearing assets).	Positive (+) and significant	Negative (-) and significant	Unit cost decreases with cumulative experience in lending to the real sector (loans).
TI	\emptyset_{Ti}	Interest on total credit.	Can be cumulated and proxied for experience in credit/risk management.	Positive (+) and significant	Negative (-) and significant	Unit cost decreases with cumulative experience in lending to the real sector.
Panel B: Inputs						
Input prices	w_s	Widgets of input prices: physical capital (sum of input prices of labour and tangible fix assets) w_p , price of deposit/debt w_d , and price of capital w_k .				
NPL	R_i	Assets quality (risk) defined as the amount of non-performing loans.				
Equity capital	K	Equity capital estimated as the sum of shareholder equity, loan loss reserve, and Tier 1 and Tier 2 capital.				

Chapter 5

Learning by Banking

Measuring Bank Experience in Credit and Value Creation: Bank-Level Evidence

5.1. Introduction

This chapter applies the framework developed in Chapter 4 to test the effect of bank experience on cost efficiency gain. Using carefully defined experience terms in the domain of credit and value creation, I investigate learning through credit and value creation in the Nigerian DMBs. The results show strong evidence of learning through investment and risk-taking (credit creation). The unit cost of producing credits decreases as more experience is gained in the production of additional credits. In terms of gross value added (measured by the efficiency of lending to the real sector and service provision), the results also show significant cost efficiency gain. This implies that experience is correlated with efficiency gain in producing gross value added. However, the results show insignificant learning through economic value creation (shareholder value creation). This implies shareholder value destruction in the Nigerian DMBs.

5.2. Data description

The total number of Nigerian commercial banks (DMBs) was reduced from 89 in 2004 to 25 in 2005 because of the bank consolidation and recapitalisation reform policy. Since 2005, there has been continuous restructuring, mergers and acquisitions, and other banking sector reforms. As of December 2019, the total number of commercial banks in Nigeria (including newly-established ones) was 22. To draw a representative sample of banks for this study, two criteria are considered: (1) top-ranked banks in terms of real assets and have at least a decade of operations, and (2) data availability. Following these two criteria, the sample size is narrowed down to the top 14 banks by capitalisation and with at least 10 years of data record.

The data generation procedure involves downloading consolidated income statements and balance sheets from each bank's website for as many years as available¹⁹. Specific

¹⁹ See Appendix A for a list of banks and the data source used for this study.

variables of interest are extracted from the annual financial statements of the 14 selected commercial banks. I build unbalanced panel data of these 14 banks from the fiscal year 2000 to 2019. The final panel length consists of 226 bank-years with approximately 3,000 bank observations. All data are adjusted for inflation using the consumer price index (CPI).

5.3. Descriptive analysis of the data

The Nigerian DMBs' financial assets and other outputs are summarised in Appendix 5A and reproduced in Figure 5.1. Net Operating Profit adjusted for Tax (NOPAT) fluctuates in response to shocks in real assets, non-performing assets, and deposits. Significant shocks in these outputs were observed between 2010–2011, perhaps in response to earlier financial distress in other economies such as the 2008/2009 Global Financial Crisis (GFC). As an import oriented and oil-dependent economy, the Nigerian economy draws its strength from developed economies such as the USA and the UK. As a result, estimates suggest that the GFC caused global credit crunch depleted the Nigerian economy in terms of private capital inflow and Nigeria capital market by 60% and 47%, respectively (CBN, 2008). Furthermore, the impact of the economic shrinkage from the GFC led to large scale default in repayment of loans as reflected in the non-performing assets observed in Figure 5.1.

Total credit flow from the DMBs seems to grow progressively with no significant shock observed. This may suggest that equity was substituted for debt (deposits) to create credit when it became difficult to raise capital to finance credit. This has become a common practise in banks around the globe and has changed the concept of modelling bank production technologies to include equity capital as bank inputs.

The direct impact of the global credit crunch on Nigeria DMBs can be seen from the two productivity measures (cost to income ratio and real assets per employee) in the first panel of Figure 5.2. The Nigerian DMBs' cost efficiency (measured by cost to income ratio) improved from approximately 60% on average to an all-time low of approximately less than 40% in 2006. This followed bank consolidation and recapitalisation policies in the Nigerian banking sector in 2005 and post the 2000s. However, the trend was reversed and

cost efficiency jumped to almost 90% in 2008 (worst record in 10 years) in the wake of the GFC.

This was again reversed as seen by the downward trend from where a record of 55% cost to income ratio was achieved in 2016, following CBN's fiscal and monetary policies and the introduction of cost-effective digital financial technologies. However, as an oil-dependent economy, the oil shock of 2018 seems to have raised the ratio to approximately 70%. Remarkably, labour productivity (real asset per employee) was affected by similar shocks, especially in 2004 and 2010.

Examining two other measures of bank performance (ROE and ROA) shows remarkable shocks between 2008 and 2011. For example, returns on equity declined from almost 40% in 2000 to -20% in 2009. Returns on assets declined from 5% in the year 2000 to below 0% in 2009 and 2011. These results agree with the earlier assertion on significant economic shocks resulting partly from the GFC.

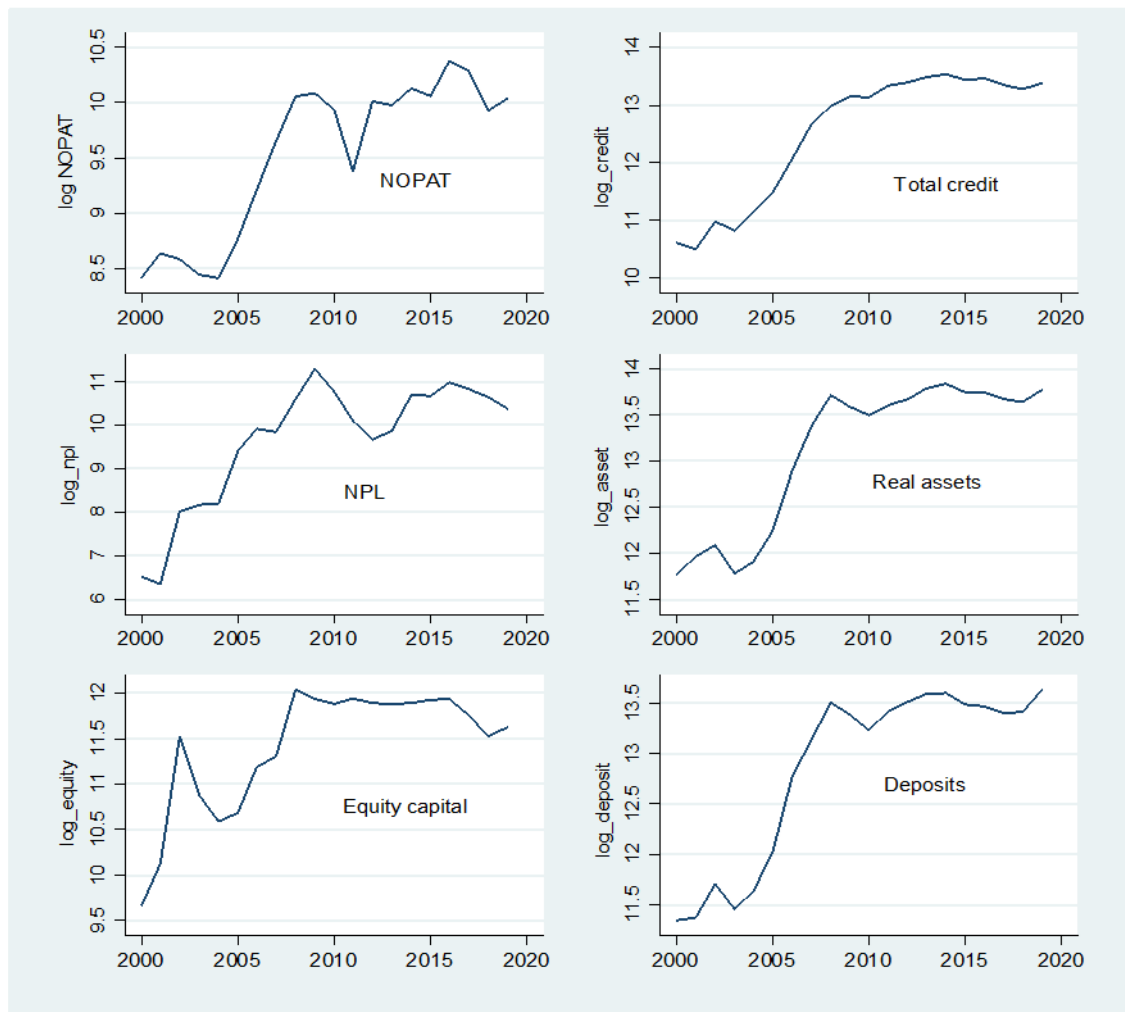


Figure 5.1. Basic outputs in Nigeria's DMBs from 2000 to 2019.

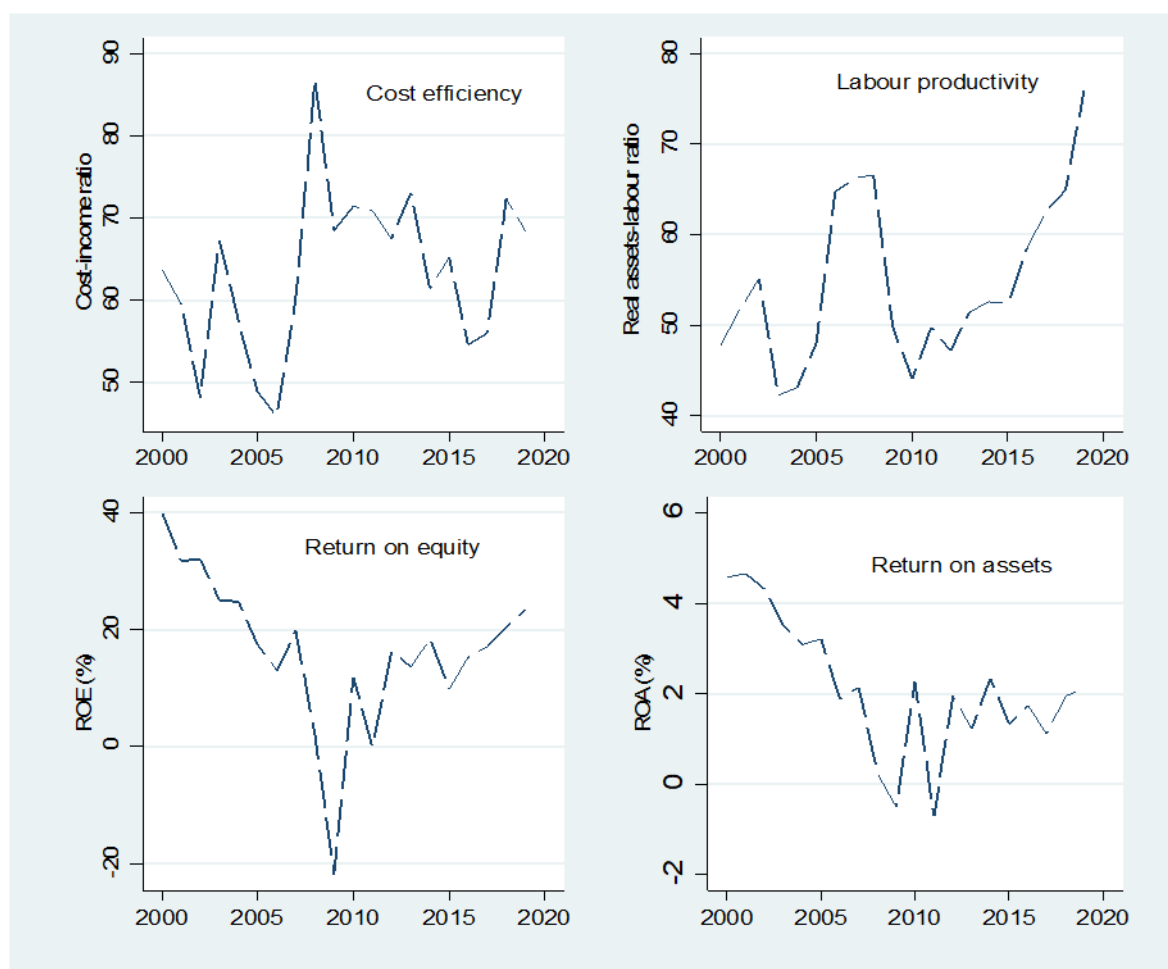


Figure 5.2. The productivity of Nigerian DMBs.

5.4. Estimation Results from the Learning Curve Models

To investigate the learning curve of the Nigerian DMBs, it is essential first to examine the relationship between unit cost and cumulative output. Figure 5.3 depicts the relationship between unit cost and various bank outputs proxied for experience terms (expressed in natural log form). The result shows decreasing unit cost as outputs expand, suggesting evidence of learning through credit (investment) and value creation in Nigerian DMBs. The relationship between unit cost and cumulative outputs shown in Figure 5.3 is quantified (estimated) using the learning models developed in Chapter 4. The results are summarised in Table 5.1.

Both panels of Table 5.1 contain the estimated results from the two learning models described earlier. Comparing the estimated learning coefficients ($\hat{\theta}_{t-1}$) of both learning models in Table 5.1 with the theoretically expected signs reveal consistent estimation in all experience terms. That is, the same variable is significant or insignificant irrespective of the learning curve model used. This consistent estimation in both models is quite instructive and, in some way, supports the robustness of the estimated results²⁰.

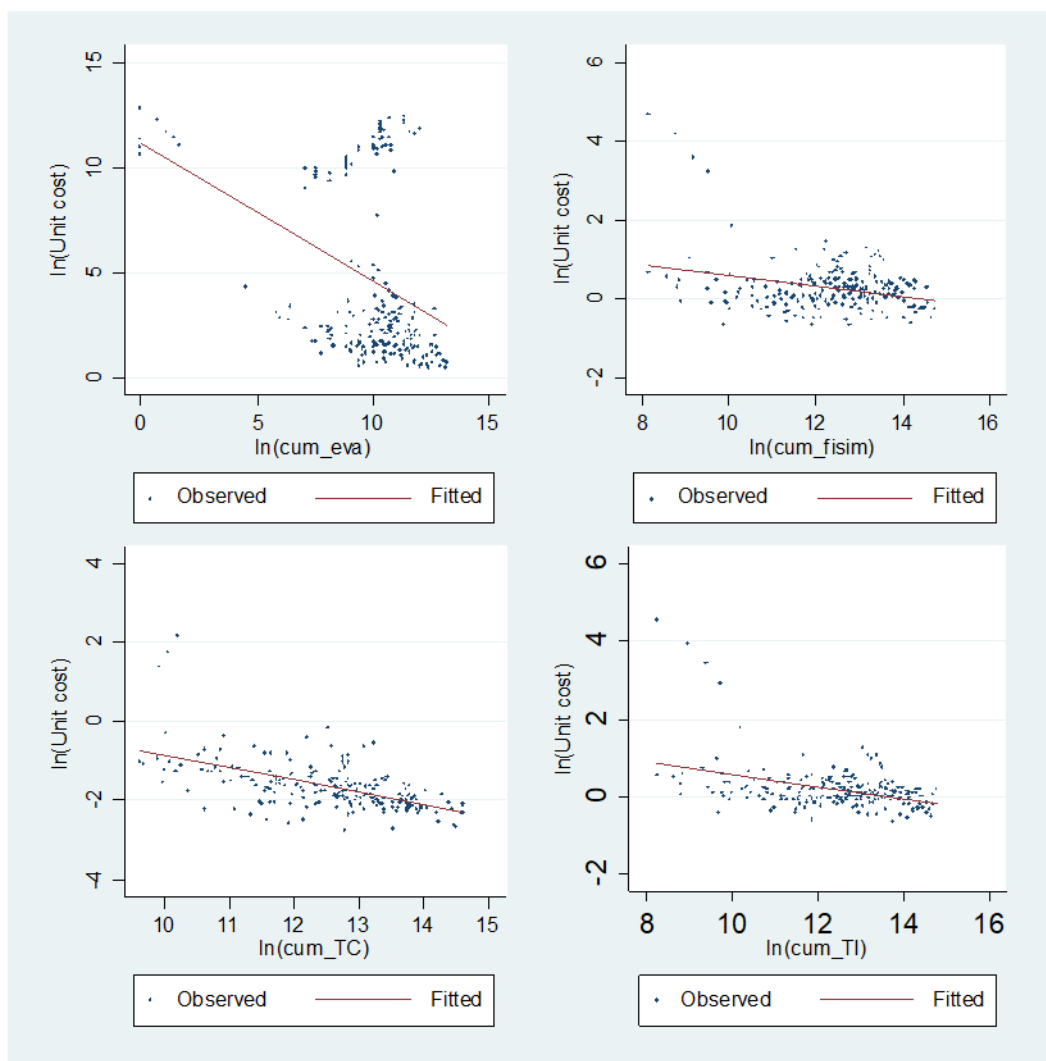


Figure 5.3. Relationship between unit cost and cumulative output.

²⁰ I discussed in detail the panel data modelling procedure in section 5.6.

Table 5.1. Estimated learning elasticities

	(1) EVA	(2) FISIM	(3) TC	(4) TII
Panel A: Dependent variable - Unit Cost				
lwp	0.7218 (0.9201)	0.4006*** (0.0738)	0.3758*** (0.0819)	0.3287*** (0.0614)
lwd	-0.8329 (0.5729)	0.2401*** (0.0537)	0.3962*** (0.0481)	0.0451 (0.0390)
lwk	1.0370*** (0.2114)	0.1103*** (0.0192)	0.1187*** (0.0207)	0.1070*** (0.0180)
lnpl	0.0707 (0.2920)	0.0096 (0.0256)	-0.0306 (0.0289)	-0.0187 (0.0156)
Year	-0.0300 (0.1410)	0.0167 (0.0158)	-0.0092 (0.0104)	0.0209 (0.0130)
$\hat{\theta}_{t-1}$	0.0214 (0.1930)	-0.0850* (0.0448)	-0.2061*** (0.0450)	-0.1447*** (0.0335)
_cons	62.5440 (282.5744)	-31.8891 (31.4994)	20.7592 (20.6220)	-39.9874 (25.9340)
Obs.	211	211	211	211
R-squared	0.1837	0.3848	0.7615	0.3607
chi2	27.4980	97.1372	179.0016	112.3847
p	0.0001	0.0000	0.0000	0.0000
rmse	3.2972	0.3028	0.3351	0.2466
Panel B: Dependent Variable - Total Cost				
lwp	0.4840*** (0.0801)	0.4407*** (0.0736)	0.4378*** (0.0591)	0.4365*** (0.0708)
lwd	0.0963* (0.0536)	0.1447*** (0.0528)	0.0156 (0.0433)	0.1430*** (0.0551)
lwk	0.1061*** (0.0151)	0.1032*** (0.0141)	0.1052*** (0.0135)	0.1018*** (0.0138)
lnpl	0.1406*** (0.0287)	0.1011*** (0.0239)	0.0817*** (0.0226)	0.1011*** (0.0245)
Year	0.0540*** (0.0137)	-0.0410** (0.0169)	0.0021 (0.0090)	-0.0543*** (0.0196)
$\hat{\theta}_{t-1}$	0.0177 (0.0166)	0.4264*** (0.0457)	0.4493*** (0.0313)	0.4430*** (0.0549)
_cons	-99.488*** (27.5343)	87.2198*** (33.6006)	-0.0557 (17.8609)	113.8203*** (38.9920)
Obs.	211	211	211	211
R-squared	0.9824	0.9845	0.9918	0.9858
chi2	166.2132	312.8808	913.5096	279.4647
p	0.0000	0.0000	0.0000	0.0000
rmse	0.2849	0.2545	0.2538	0.2579

Standard errors are in parenthesis.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Prais-Winsten regression, correlated panels corrected standard errors (PCSEs).

Panels: correlated (unbalanced).

Autocorrelation: panel-specific AR (1).

Sigma computed by case-wise selection.

5.4.1. Learning through Value Creation

To describe the economic implications of the estimated learning results, I reproduce the results in Panel A of Table 5.1 and calculate other parameters based on the learning curve theory. The results and the hypothesis can be found in Table 5.2.

Two proxies of value creation in banks are used to investigate learning in the domain of value created in the sample of banks studied, namely EVA and FISIM. The former emphasises the efficiency of shareholder capital utilisation (returns on investment), or the true economic profit and benefit to the shareholders. The latter emphasises the gross output value created as a result of productive activities of the banks at a given time²¹.

The results in Table 5.2 show insignificant learning in the domain of EVA. This suggests that the unit cost of creating additional economic value-added does not decrease with experience. As a proxy for learning by shareholder value creation, this result suggests inefficiency in shareholder value creation in Nigeria DMBs and could mean shareholder value destruction. It also means that considering all economic costs and the opportunity cost of capital, the shareholder value in Nigerian DMBs has been substantially destroyed. This is also evident from the negative EVAs recorded by the banks in some years as seen in Appendix 5F.

In terms of FISIM, the result is significant. This indicates that experience is correlated with gross value-added, that is, unit cost decreases as more experience is gained in producing gross value added. More specifically and quantitatively, FISIM has a progress ratio of $\delta_t = 94\%$. This implies that unit cost decreased by 5.6% annually on average, other things being equal, due to experience acquired in producing gross value added. However, as noted by the min-max values, the progress ratios fluctuate from year to year and from bank to bank.

²¹ As noted earlier, FISIM is the risk adjust gross value added based on the SNA 2008 framework that considers only productive activities of banks at a given time. The inputs used for estimating FISIM excludes returns from banks own fund because this may not constitute a productive action at the time of evaluation.

5.4.2. Learning through Credit Creation (Investment and Risk-Taking)

Credit creation constitutes significant activities of commercial banks and may include activities such as loans, investment, risk redistribution, and debt management. Here, I address the question of how experience could affect financial intermediary efficiency in general. More specifically, I look at how bank experience could offset the cost of credit creation and debt management. Credit creation is proxied for total loans plus other investment produced annually. The results show that there is significant evidence of learning through credit creation (column 3, Table 5.3). The alternative measure of this learning proxied by cumulative interest income accrued to total investment also shows significant learning by credit creation (column 4). The learning rates associated with these experience terms show that at least 8% to 14% cost was saved on average between 2001 to 2019 as more knowledge about risk management in assets and portfolios gained from experience are channelled into credit creation. This implies learning through investment and risk-taking.

Table 5.2. Estimated progress ratio/learning rates of Nigeria DMBs

	(1) EVA	(2) FISIM	(3) Total Credit	(4) TI
Dependent variable: Unit Cost				
$\hat{\phi}_{t-1}$	0.0214 (0.2132)	-0.0850* (0.0448)	-0.2061*** (0.0450)	-0.1447*** (0.0335)
Hypothesis	Reject	Do not reject	Do not reject	Do not reject
Average Estimated Progress Ratios				
δ_t	1.015	0.944	0.857	0.918
$\delta_t(\%)$	101.5	94.40	85.70	91.80
$100-\delta_t(\%)$	-1.5	5.60	14.30	8.20
Cost implication	Increased	reduced	reduced	reduced
Std. Dev.		0.069	0.044	0.052
Min		0.824	0.771	0.815
Max		1.043	0.905	0.978

Standard errors are in parenthesis.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

$\delta_t = 2^{\hat{\phi}_t}$, if $\hat{\phi}_t$ is significant.

5.4.3. Dynamic learning-by-doing in Nigerian DMBs

Results in Table 5.2 provide average (fixed) estimates of learning rates across all banks for the entire period covered. However, the results do not represent the dynamic annual

learning/experience in the financial intermediating activities of these banks. The empirical literature on learning curves shows that learning is dynamic and can vary over time. Similarly, it can be argued that bank learning in the domain of credit and value creation (asset transformations) is not static.

To show the dynamics of learning through credit and value creation in Nigerian DMBs along the years, I use the cubic approximation of the learning model. Here, I assume that unit cost can be best represented by a log-linear cubic learning function²². This model enables us to disentangle the dynamic annual learning rates within and across bank samples. The estimated annual learning rates are summarised in Table 5.3.

Table 5.3. Annual learning rates/progress ratios of Nigerian DMBs

Year	FISIM		Total Credit (TC)		Total Interest Income (TII)	
	δ_t	$(1 - \delta_t) \times 100$	δ_t	$(1 - \delta_t) \times 100$	δ_t	$(1 - \delta_t) \times 100$
2001	0.899	10.1	0.789	21.1	0.827	17.3
2002	1.023	-2.3	0.771	22.9	0.904	9.6
2003	0.866	13.4	0.821	17.9	0.826	17.4
2004	0.824	17.6	0.777	22.3	0.815	18.5
2005	0.899	10.1	0.806	19.4	0.870	13.0
2006	0.938	6.2	0.819	18.1	0.891	10.9
2007	1.013	-1.3	0.897	10.3	0.939	6.1
2008	1.019	-1.9	0.905	9.5	0.949	5.1
2009	1.043	-4.3	0.898	10.2	0.975	2.5
2010	1.029	-2.9	0.889	11.1	0.978	2.2
2011	1.013	-1.3	0.888	11.2	0.974	2.6
2012	0.995	0.5	0.887	11.3	0.968	3.2
2013	0.973	2.7	0.883	11.7	0.960	4.0
2014	0.952	4.8	0.876	12.4	0.951	4.9
2015	0.931	6.9	0.871	12.9	0.941	5.9
2016	0.910	9.0	0.876	12.4	0.931	6.9
2017	0.892	10.8	0.877	12.3	0.923	7.7
2018	0.873	12.7	0.874	12.6	0.914	8.6
2019	0.846	15.4	0.883	11.7	0.901	9.9

The results show that unit cost decreases as experience doubles for all outputs and in all years under investigation, except in gross output (FISIM) where cost efficiency was lost

²² See equation (4.30) in chapter 4 for details of the cubic learning function.

in 2002 and between 2007 to 2011. The unit cost of producing an additional gross value added increased by 2.3% in 2002. A similar inference holds for years 2007–2011 where progress ratios were greater than 1.0.

The cost implication calculated from the annual learning rates in Table 5.3 can be graphically illustrated using Figure 5.4 to understand the trend. The graphical illustrations in Figure 5.4 show that there are some economic implications in terms of cost efficiencies in credit and value creation. First, cost efficiencies fluctuate and seem to be affected by shocks in the year 2002, and between 2007 and 2011 in the case of FISIM. During these years, the productivity of gross value added was negative (-2.3% on average). This implies losses in cost efficiency or the learning process due to internal or external shocks. The cost-efficiency associated with interest income was also significantly affected by similar shocks. This resulted in losses of cost efficiency from 17.4% in 2001 to 2.5% in 2009 and 2.2% in 2010.

The efficiency of credit creation was stable and did not seem to be significantly affected by any shocks. As argued earlier, banks can substitute equity for debt financing in situations where raising capital through other means proves difficult.

In summary, the results show that learning is dynamic and varies across time. In hindsight, external shocks, such as 2001 and the GFC, and other internal shocks may have affected the productivity of Nigerian commercial banks in terms of the efficiency of credit created and the gross value added to the economy.

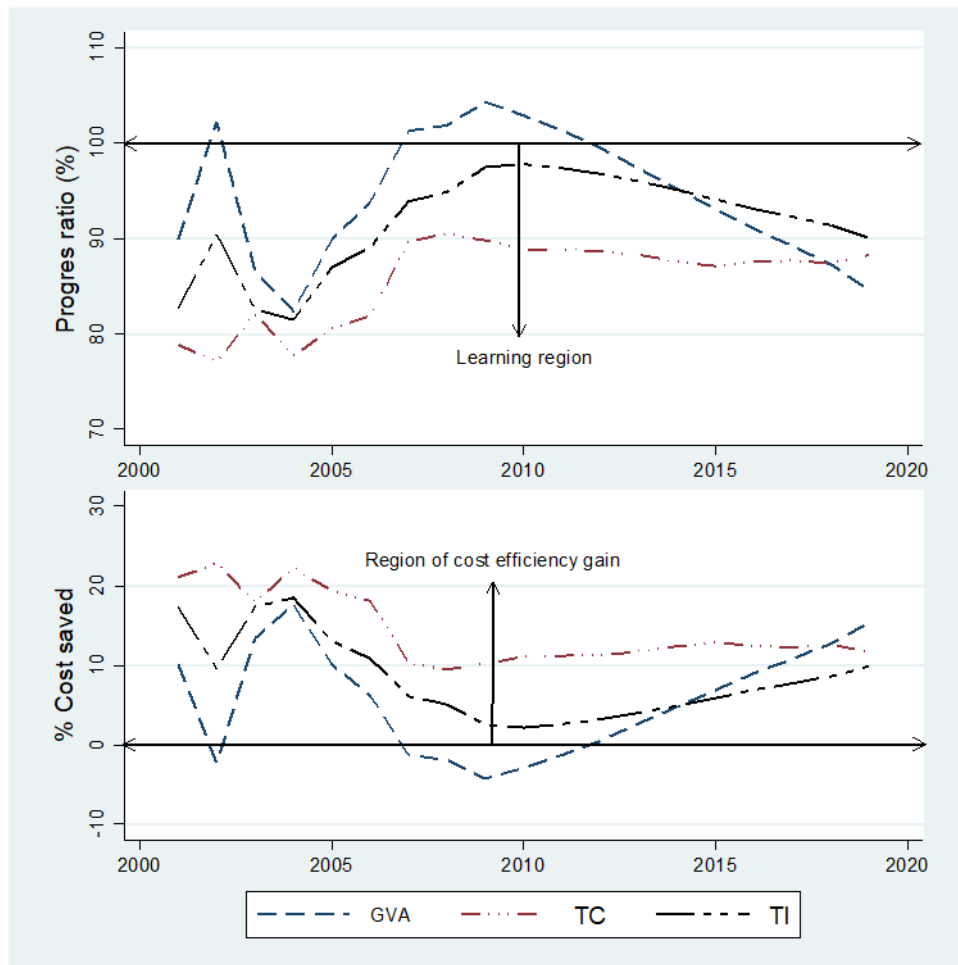


Figure 5.4. Annual learning rates in Nigerian DMBs.

5.5. Discussion and conclusion

In this study, I have argued that value and credit creation are two essential roles of banks and that banks must create value to remain in business. The banking sector has been described as ‘the engine of economic growth’. The economic value-added and the FISIM are among the most reliable value-based measurement (VBM) tools used for evaluating shareholder value and stakeholder (the gross) value created.

EVA has been described to have the strongest correlation with market value-added. EVA offers a better evaluation of banks’ risk dynamics: unify management financial activities, provide the basis for investment justification, align management objectives towards

corporate goals of shareholder and stakeholder value enhancement, align employee behaviour with wealth creation, encourage capital discipline, and most importantly, discourage/eliminate the presence of free-riders, that is, divisions with little or no value-enhancing contributions (Bhasin, 2013; Uyemura et al., 1996).

From an economic and policy perspective, gross value added from the banking sector measured by FISIM shows the extent of productive activities of banks such as deposit-taking and lending to the real sector.

The value creation process in banks is a trade-off between different bank actions, the resultant payoff of these actions, and how soon the payoffs are realised. While value determinants such as aggressive efficiency programs, reduction of capital investment, and aggressive risk-taking to increase net operating profit may be value-enhancing, they can adversely off-set bank value creation through reduced customer satisfaction, increased business risk, and increased opportunity cost of capital, respectively (Fiordelisi & Molyneux, 2010).

This study is an attempt to capture the trade-off or knowledge acquired through bank intermediary activities. The results show that the unit cost of producing additional shareholder value increases as output doubles. This suggests efficiency loss and provides compelling evidence of value destruction over time. This might also be a pointer to the presence of units not making a value-enhancing contribution.

Gross value added resulting from the productive activities of banks in deposit-taking and lending to the real sector suggests that Nigerian DMBs efficiently channel available credit to the real sector. Relatedly, there is also efficiency gain in credit creation as demonstrated by learning in the domain of total credit created and the interest generated.

5.6. Panel data procedure

In the panel data modelling, I follow some necessary procedures to ensure consistent and robust estimation. First, the model specification test for each regression using a robust Hausman test favours the fixed-effect model. Second, diagnostic tests suggest that the data suffer from autocorrelation, heteroskedasticity, and spatial cross-sectional dependence (see Table 5.4). With the cross-sectional units less than the time dimension,

two estimators of data modelling come to mind: feasible generalised least-squares (FGLS) and panel-corrected standard error (PCSE). Robust or cluster standard errors with FGLS based on the algorithms of Parks (1967), Wickens and Kmenta (1972), and Kmenta (1986) could correct these violations. However, the unbalanced nature of the panel data do not allow for estimation with a correlated error structure. Therefore, I implement the Prais-Winsten estimator with panel-corrected standard error (PCSE) and panel specific autocorrelation. Moreover, this estimator has been found to outperform other estimators for short panel data modelling when the purpose of estimation is hypothesis testing (Moundigbaye et al., 2018; Reed & Ye, 2011)

Table 5.4. Checking for violation of the basic assumption of panel data modelling

	Born and Breitung (2016) Q(p)-test		Born and Breitung (2016) LM(k)-test		Born and Breitung (2016) HR-test		Pesaran (2015)	
	Ho: No serial correlation up to order p.				Ho: No first-order serial correlation		Ho: Cross-section independence	
Variable	Q (2)-stat	p-value	LM (2)- stat	p-value	HR-stat	p-value	CD-test	p-value
lQeva	8.930	0.012	2.280	0.023	-3.780	0.000	29.803	0.000
lQfisim	54.170	0.000	5.620	0.000	-6.210	0.000	34.284	0.000
lQTC	40.240	0.000	4.530	0.000	-3.250	0.001	25.084	0.000
lQTI	92.920	0.000	6.060	0.000	-6.930	0.000	34.453	0.000

Appendix 5A

The sample of banks and data sources used for this study

Bank	Data availability (years)	Data Source
Access bank Plc	17	https://www.accessbankplc.com/
Diamond bank Plc	17	http://www.diamondbank.com/
First bank of Nigeria Plc	15	https://www.firstbanknigeria.com/
First city monument bank Plc	17	http://www.fcmb.com/
Fidelity Plc	17	https://www.fidelitybank.ng/
Guarantee trust bank Plc	18	http://www.gtbank.com/
Stanbic IBTC Plc	18	https://www.stanbicibtcbank.com/
Sterling Plc	13	https://sterling.ng/
Skye bank Plc	11	https://www.polarisbanklimited.com/
United bank for Africa Plc	18	https://www.ubagroup.com/
Union bank Plc	14	https://www.ubagroup.com/
Unity bank Plc	14	https://www.unitybankng.com/
Wema Plc	18	https://www.wemabank.com/
Zenith bank Plc	20	https://www.zenithbank.com/

Appendix 5B

Average growth of assets and other banks' outputs

year	NOPAT	Total Credit	Real Assets	Deposits	Equity capital	NPL	NPL%	ROE	ROA	CtR%	RtL%
2000	4,538.06	40,901.02	129,196.13	84,575.61	15,766.50	682.42	1.67	39.92	4.57	63.73	47.78
2001	5,659.69	36,464.68	157,325.89	87,212.87	25,006.06	571.23	1.57	31.84	4.66	59.56	51.80
2002	5,350.82	58,713.31	177,136.18	121,337.57	101,695.10	3,051.48	5.20	32.05	4.32	48.09	55.16
2003	4,655.87	50,288.68	131,222.72	95,219.49	52,842.50	3,510.83	6.98	25.04	3.52	67.26	42.26
2004	4,523.36	69,274.44	148,516.24	113,051.84	39,846.60	3,646.85	5.26	24.80	3.10	57.38	43.09
2005	6,489.11	97,263.00	207,334.71	166,205.21	43,770.38	12,106.64	12.45	17.48	3.21	48.89	48.10
2006	10,001.97	173,899.19	396,185.29	349,052.57	72,169.96	20,253.62	11.65	13.02	1.89	45.93	64.76
2007	15,648.28	317,309.62	645,803.07	507,290.54	81,368.89	18,596.45	5.86	19.84	2.15	60.37	66.25
2008	23,311.71	434,630.36	903,314.26	733,597.95	168,717.00	40,054.70	9.22	1.89	0.25	86.89	66.60
2009	23,976.09	513,923.61	796,319.37	651,909.67	152,424.20	80,073.57	15.58	-21.93	-0.49	68.45	49.78
2010	20,625.30	509,158.71	724,471.43	557,238.36	144,502.90	47,484.86	9.33	11.87	2.26	71.44	44.06
2011	11,901.88	621,551.70	807,231.20	672,249.61	153,781.00	24,130.21	3.88	0.07	-0.71	70.85	49.77
2012	22,321.96	653,119.07	862,204.81	736,534.93	146,387.20	15,785.16	2.42	16.24	1.96	67.47	47.21
2013	21,490.44	722,171.80	971,259.66	799,663.32	145,056.20	19,260.29	2.67	13.67	1.22	73.08	51.47
2014	25,104.98	751,654.70	1,021,501.10	802,717.25	145,932.40	43,800.10	5.83	18.46	2.34	61.42	52.63
2015	23,494.15	689,452.79	926,868.82	718,111.97	151,240.10	42,767.84	6.20	9.83	1.34	65.23	52.39
2016	32,138.48	701,325.91	926,695.34	705,473.38	152,818.30	58,898.87	8.40	15.32	1.75	54.58	58.52
2017	29,429.65	623,162.72	861,117.41	659,975.19	127,966.50	49,876.34	8.00	17.18	1.12	55.96	62.60
2018	20,561.90	586,523.06	836,843.45	668,551.86	101,450.90	41,924.59	7.15	20.37	1.96	72.37	64.92
2019	22,912.55	646,068.46	959,901.69	829,523.74	112,205.50	32,171.77	4.98	23.42	2.11	68.37	75.93

CtR is cost to income ratio

RtL is real assets to labour ratio

Appendix 5C

Estimated full trans log cost function

ltc	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
lnY	0.3301	0.4704	0.70	0.483	-0.592	1.252	
lnY ²	-0.1208	0.0475	-2.54	0.011	-0.214	-0.028	**
lnw1	-0.3185	0.2348	-1.36	0.175	-0.779	0.142	
lw2	0.9046	0.4762	1.90	0.058	-0.029	1.838	*
lE	0.3837	0.3584	1.07	0.284	-0.319	1.086	
t	0.0978	0.0545	1.80	0.073	-0.009	0.205	*
lw1_2	0.0061	0.0170	0.36	0.720	-0.027	0.039	
lw2_2	0.1917	0.0668	2.87	0.004	0.061	0.323	***
lE_2	-0.1575	0.0497	-3.17	0.002	-0.255	-0.060	***
t_2	0.0048	0.0015	3.19	0.001	0.002	0.008	***
lylw1	0.1211	0.0226	5.35	0.000	0.077	0.165	***
lylw2	-0.1128	0.0654	-1.72	0.085	-0.241	0.016	*
lylE	0.1596	0.0273	5.84	0.000	0.106	0.213	***
tly	-0.0114	0.0056	-2.03	0.042	-0.022	-0.000	**
lw1lw2	-0.0181	0.0306	-0.59	0.554	-0.078	0.042	
lw1lE	-0.1012	0.0229	-4.41	0.000	-0.146	-0.056	***
lw2lE	0.1701	0.0551	3.09	0.002	0.062	0.278	***
tlw1	-0.0019	0.0040	-0.47	0.639	-0.010	0.006	
tlw2	-0.0012	0.0079	-0.15	0.878	-0.017	0.014	
Constant	1.9512	2.2830	0.85	0.393	-2.523	6.426	
μ	0.1960	0.1249	1.57	0.117	-0.049	0.441	
lnσ	-2.9273	0.3501	-8.36	0.000	-3.614	-2.241	***
ilgy	-0.1199	0.7478	-0.16	0.873	-1.585	1.346	
sigma2	0.0535	0.0187			0.026	0.106	
gamma	0.4700	0.1862			0.170	0.793	
sigma_u2	0.0251	0.0186			-0.011	0.061	
sigma_v2	0.0283	0.0027			0.022	0.033	
Mean dependent variable		9.2424	SD dependent var			0.8906	
Number of obs		225.0000	Chi-square			3888.8263	
Prob > chi2		0.0000	Akaike crit. (AIC)			-84.2779	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix 5E

Estimated learning elasticities using alternative model (eqn. 4.24)

Dependent variable: Total cost

	(1) EVA	(2) FISIM	(3) TC	(4) TII
Panel A: Controlled for year trend				
lwp	0.4840*** (0.0801)	0.4407*** (0.0736)	0.4378*** (0.0591)	0.4365*** (0.0708)
lwd	0.0963* (0.0536)	0.1447*** (0.0528)	0.0156 (0.0433)	0.1430*** (0.0551)
lwk	0.1061*** (0.0151)	0.1032*** (0.0141)	0.1052*** (0.0135)	0.1018*** (0.0138)
lnpl	0.1406*** (0.0287)	0.1011*** (0.0239)	0.0817*** (0.0226)	0.1011*** (0.0245)
Year	0.0540*** (0.0137)	-0.0410** (0.0169)	0.0021 (0.0090)	-0.0543*** (0.0196)
$\hat{\theta}_{t-1}$	0.0177 (0.0166)	0.4264*** (0.0457)	0.4493*** (0.0313)	0.4430*** (0.0549)
_cons	-99.488*** (27.5343)	87.2198*** (33.6006)	-0.0557 (17.8609)	113.8203*** (38.9920)
Obs.	211	211	211	211
R-squared	0.9824	0.9845	0.9918	0.9858
chi2	166.2132	312.8808	913.5096	279.4647
p	0.0000	0.0000	0.0000	0.0000
rmse	0.2849	0.2545	0.2538	0.2579
Panel B: Controlled for time fixed effect				
lwp	0.3727*** (0.0738)	0.3692*** (0.0668)	0.4397*** (0.0649)	0.3724*** (0.0643)
lwd	0.1135** (0.0527)	0.1891*** (0.0430)	-0.0031 (0.0417)	0.1805*** (0.0454)
lwk	0.1168*** (0.0183)	0.1149*** (0.0161)	0.1267*** (0.0156)	0.1141*** (0.0156)
lnpl	0.1006*** (0.0308)	0.0692*** (0.0254)	0.0496** (0.0250)	0.0688*** (0.0246)
$\hat{\theta}_{t-1}$	0.0104 (0.0158)	0.4635*** (0.0315)	0.4582*** (0.0393)	0.5142*** (0.0382)
_cons	9.0140*** (0.4080)	5.2597*** (0.3750)	4.3459*** (0.4421)	4.8698*** (0.4232)
Obs.	211	211	211	211
R-squared	0.9853	0.9947	0.9953	0.9941
chi2	2003.9241	1344.5220	3755.6454	970.8573
p	0.0000	0.0000	0.0000	0.0000
rmse	0.2551	0.2276	0.2387	0.2302
FE	Yes	Yes	Yes	Yes

Standard errors are in parenthesis

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Prais-Winsten regression, correlated panels corrected standard errors (PCSEs)

Panels: correlated (unbalanced)

Autocorrelation: panel-specific AR(1)

Sigma computed by case-wise selection

Appendix 5D

Estimated learning elasticities using the learning model (eqn. 4.25)

Dependent Variable: Unit Cost

	(1) EVA	(2) FISIM	(4) TC	(6) TII
Panel A: Controlled for time trend				
lwp	0.7218 (0.9201)	0.4006*** (0.0738)	0.3758*** (0.0819)	0.3287*** (0.0614)
lwd	-0.8329 (0.5729)	0.2401*** (0.0537)	0.3962*** (0.0481)	0.0451 (0.0390)
lwk	1.0370*** (0.2114)	0.1103*** (0.0192)	0.1187*** (0.0207)	0.1070*** (0.0180)
lnpl	0.0707 (0.2920)	0.0096 (0.0256)	-0.0306 (0.0289)	-0.0187 (0.0156)
Year	-0.0300 (0.1410)	0.0167 (0.0158)	-0.0092 (0.0104)	0.0209 (0.0130)
$\hat{\theta}_{t-1}$	0.0214 (0.1930)	-0.0850* (0.0448)	-0.2061*** (0.0450)	-0.1447*** (0.0335)
_cons	62.5440 (282.5744)	-31.8891 (31.4994)	20.7592 (20.6220)	-39.9874 (25.9340)
Obs.	211	211	211	211
R-squared	0.1837	0.3848	0.7615	0.3607
chi2	27.4980	97.1372	179.0016	112.3847
p	0.0001	0.0000	0.0000	0.0000
rmse	3.2972	0.3028	0.3351	0.2466
Panel B: Controlled for time fixed effect				
Lwp	0.3467 (0.9373)	0.3620*** (0.0747)	0.4200*** (0.0934)	0.3272*** (0.0662)
lwd	-0.5698 (0.6870)	0.2554*** (0.0589)	0.3681*** (0.0553)	0.0695 (0.0440)
lwk	1.1461*** (0.2107)	0.1087*** (0.0206)	0.1126*** (0.0209)	0.1073*** (0.0193)
lnpl	-0.2481 (0.3737)	0.0374 (0.0257)	-0.0567 (0.0373)	-0.0130 (0.0172)
$\hat{\theta}_{t-1}$	-0.1361 (0.2132)	-0.1385*** (0.0378)	-0.1688*** (0.0543)	-0.1494*** (0.0305)
_cons	5.8226 (5.6761)	1.6658*** (0.4339)	2.3891*** (0.5550)	1.8258*** (0.3635)
Obs.	211	211	211	211
R-squared	0.3222	0.4836	0.8033	0.4132
chi2	211.3897	638.0212	394.6396	249.6257
p	0.0000	0.0000	0.0000	0.0000
rmse	3.1360	0.2919	0.3247	0.2468
FE	Yes	Yes	Yes	Yes

Standard errors are in parenthesis

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Prais-Winsten regression, correlated panels corrected standard errors (PCSEs)

Panels: correlated (unbalanced)

Autocorrelation: panel-specific AR(1)

Sigma computed by casewise selection

Appendix 5F

Descriptive statistics of some outputs

Variable		Mean	Std. Dev.	Min	Max	Observations		
						N	n	T-ba
EVA	overall		37382.63	-352332.70	75505.40	225	14	16.07
	between	2147.25	19690.57	-39980.96	30478.58			
	within		32053.29	-310204.50	67790.63			
FISIM	overall		50560.84	3073.89	223349.70	225	14	16.07
	between	62932.03	38219.34	15593.28	146204.10			
	within		33877.94	-38910.41	161376.50			
NOPAT	overall		20740.53	-56777.41	94798.25	225	14	16.07
	between	18961.31	15274.51	950.59	50452.46			
	within		14348.33	-43299.49	65747.45			
Interest income	overall		55253.61	3281.21	239554.20	225	14	16.07
	between	69675.09	40900.64	19256.50	173220.50			
	within		38611.63	-44161.35	169853.00			

Chapter 6

Technological Learning in the Nigerian Financial System I

~ Forecasting the diffusion of electronic payments systems in Nigeria ~

6.1. Introduction

This chapter analyses the diffusion of electronic payment technologies and forecasts the future trajectories of these technologies. The four major electronic payments technologies in Nigeria considered here include ATM, POS, Mobile, and Web payment. Using diffusion models, this chapter first analyses the phase development of these four major financial technologies related to EPSs in Nigeria. Second, this chapter describes how these technologies compete within the payment system niche market, forecasts their future possible market share, and discusses how they decline using technology substitution model.

6.2. Background of the study

Advances in financial technologies and innovations have transformed how financial services can be accessed, especially in developing countries. Financial access has become easy, with far-reaching economic implications, due to the introduction of innovative digital financial technologies and services (IMF & World Bank, 2018; Lee et al., 2020; Ozili, 2018; Senyo & Osabutey, 2020; Yao et al., 2018). These financial technologies were introduced to various economies at various times. However, unlike the financially developed economies, the diffusion of these technologies is still at infancy in developing economies. Hence, these technologies have the prospect of transforming the financial and economic landscape of these economies. Moreover, the narrowing digital divides in developing countries in recent times have arguably facilitated the proliferation and adoption of these technologies (Nguena, 2019; Pazarbasioglu et al., 2020; Wolbers, 2017).

6.3. The paradigm shift in the Nigerian payment landscape

In the early 2000s, the CBN was confronted with an emerging monetary challenge: the rising cost of cash. The direct cost of cash to the Nigerian financial system during this time was on the rise and was projected to rise from USD 300 million in 2008 to approximately USD 1.28 billion in 2012, a staggering 66% increase per annum (CBN,

2010). As a result, the central bank introduced several monetary policies to reduce the cost of cash to Nigeria's economy (Atanda et al., 2012; Ezeamama et al., 2014). The prominent ones among these policies were Cashless Nigeria, Mobile Payment Systems, and the Payment System Vision 2020. Taking advantage of the rapid penetration of digital supporting infrastructure such as mobile phones, internet, and other ICTs, these policies became the enablers for the proliferation and diffusion of digital non-cash and electronic payment technologies. A decade on, and in response to emerging financial innovations, the Nigerian payment landscape has witnessed tremendous disruption (Figure 6.1) and has generated interests from academics (Ezeamama et al., 2014; Jatau & Dung, 2014; Taiwo & Agwu, 2017; John et al., 2020).

The first panel of Figure 6.1 is the flowchart of Nigeria's payments system, made up of cash, non-cash, and electronic payments. As noted, promoting the adoption of the non-cash and the electronic payments was a matter of policy thrust, given the resulting benefits (Adu, 2016; Ene et al., 2019; Joseph & Richard, 2015). The apex bank identified the electronic payment media as the most important future payment technologies that could reduce the currency outside of bank (COB), increase access to financial products/services, enable financial integration and inclusion, eliminate shadow economies, and stimulate economic growth and development (Atanda & Alimi, 2012; CBN, 2011). Electronic payments allow access to a variety of financial products, permit a variety of financial exchanges, and provide transaction efficiency to individuals, firms, and the economy. The second panel of Figure 6.1 illustrates the mechanism of electronic payments in the simplest form. The economic agents include providers (financial institutions, telecoms, approved agents, and technology/infrastructure providers) who are responsible for end-to-end transaction on the platform, users who initiate or access payment services, and regulators who provide the policy framework and regulate the operation of the payment ecosystem.

Figure 6.2 shows the proliferation of these payment platforms. These platforms rose from 5 in 2009 to 9 in 2014, and finally to 12 in 2017. According to the CBN, the motivation for introducing these nascent non-cash payment schemes was because they facilitate person-to-person, person-to-business, and business-to-business financial transactions with minimal risk, besides providing flexible financial services to both banked and

unbanked population. These non-cash EPSs have been growing significantly within the last decade. For example, according to the electronic payments' factsheet, the total value of electronic payments transacted rose from USD 133.4 billion in 2010 to USD 345 billion in 2019, an approximately three-fold increase within a decade (Ajiboye et al., 2013; NIBSS, 2019).

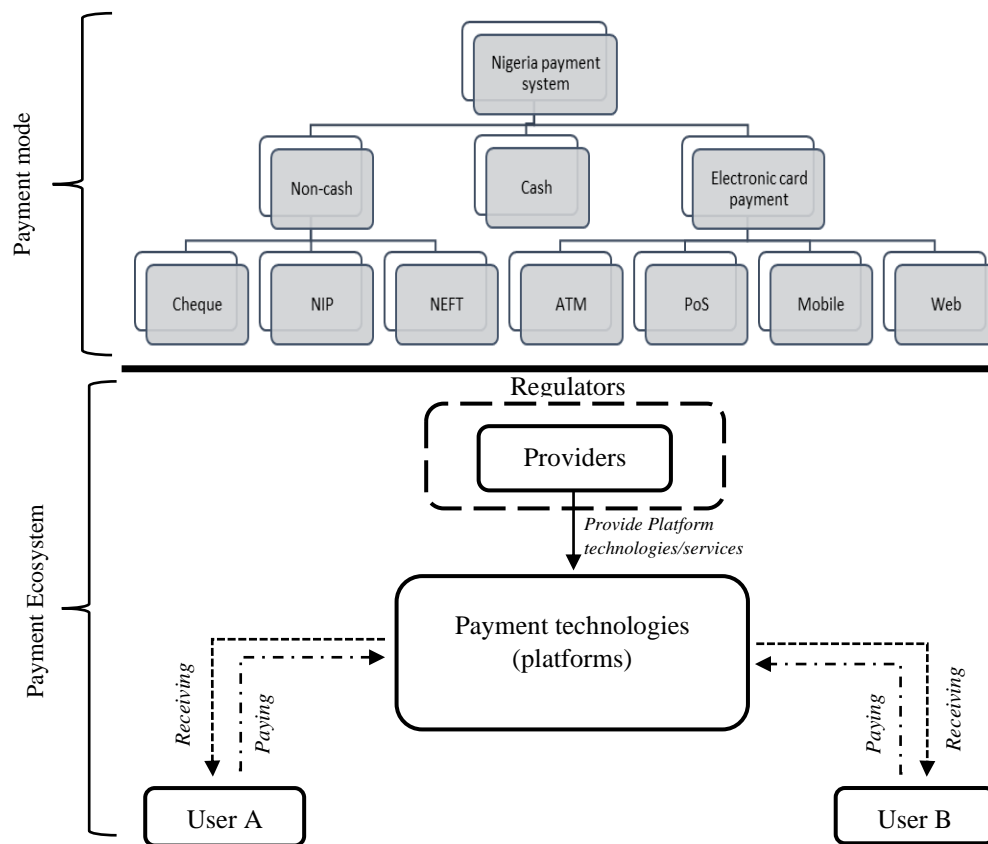


Figure 6.1. The Nigerian payments system (Source: authors).

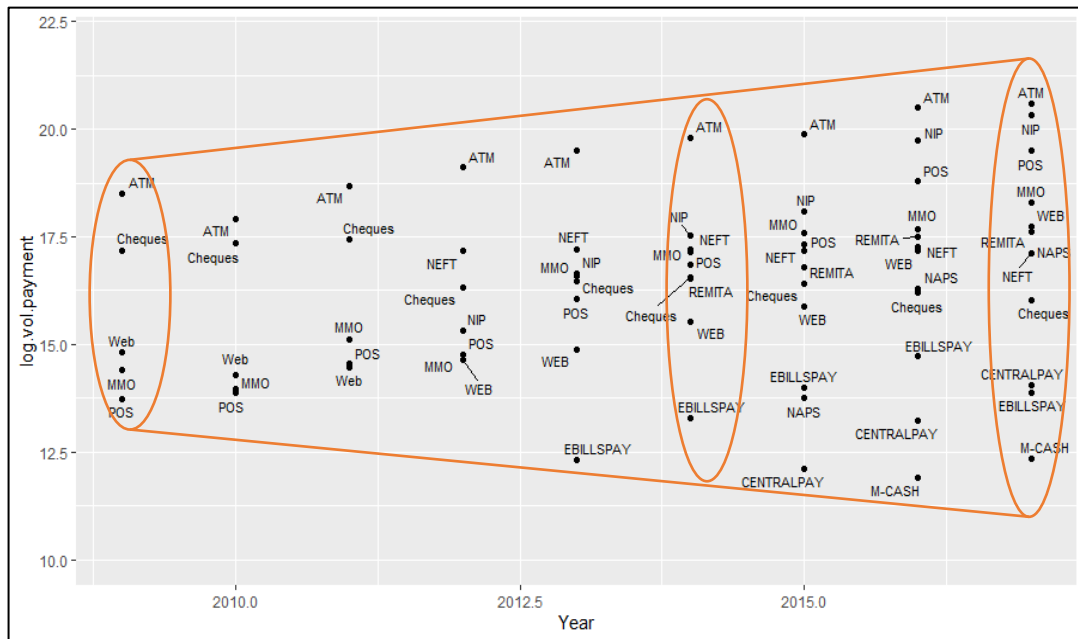


Figure 6.2. Proliferation in the Nigerian payments system (Source: authors).

6.4. Technological forecasting: A brief review

Forecasting, when applied to technology, is the process of observing technological innovations and determining the sequence of events in the lifecycle of the technology. Technology forecasting represents the ‘systematic attempts to anticipate and understand the direction, rates, characteristics and effects of technological change, especially as it concerns the adoption and use of technologies’ (Martino, 2003; Coates et al., 2001)²³. Forecasting the diffusion of technologies [innovations] plays a significant role in the development and improvement of either the same technologies or the introduction of new competing technologies. Many technology forecasting techniques used for analysing a wide range of technologies across a spectrum of industries have been identified in the literature (Coates et al., 1993). These techniques provide necessary information that helps in understanding the growth pattern of technologies and the industry characteristics (Lee et al., 2011; Adamuthe & Thampi, 2019). The motivation for technology forecasting is to respond to the emerging needs of economic agents in our dynamic and competitive global business environment, and the recognition of the role and contribution of technology to economic growth. As a result, the practice of forecasting technology diffusion remains a

²³ Technology diffusion also refers to the spread of technology into the market and the subsequent adoption among end users.

critical research agenda for practitioners as long as new technologies are continually introduced into the market.

The diffusion of technologies follows continuous trajectories of growth and declines over time. These trajectories are often described with S-shaped curves (diffusion models) and are sometimes characterised by four phases: introduction, growth, maturity, and decline (Kraja & Braimllari Spaho, 2019; Kucharavy & De Guio, 2011; Lotfi et al., 2014; Meyer et al., 1999). The parameters of most S-shaped curves (especially those of the logistic family) contain sufficient information to inform managers on the current phase development, and the future performance of technologies. In terms of competing innovations or technologies in a niche market, technology forecasters have used the cumulative number of adoptions of individual technology to understand how they compete, substitute, and naturally phase-out. This process is called technology substitution.

Diffusion models such as logistic and Gompertz models have been described as accurate and straightforward growth models due to the ease with which their parameters can be interpreted (Kucharavy & De Guio, 2011; Windarto et al., 2018). For example, estimates from these diffusion models show the speed of diffusion of a technology or innovation and the saturation level or market carrying capacity (Kraja & Braimllari Spaho, 2019). As a result, these models are traditionally used to forecast new product demand, measure product life cycle dynamics, and sometimes as strategic decision-making tools for market evaluation and penetration (Meade & Islam, 2006). Moreover, the logistic model has been described as ‘possessing the natural law of technology diffusion with considerable success as an empirically descriptive and heuristic device that can capture the changing nature of technologies, products, markets and industries’ (Devezas, 2005). This study reviews and adopts these diffusion models.

6.5. Research methods: Forecasting technologies with growth models

Technology growth models are based on the technology life cycle theory, which in general explains how technologies advance and diffuse over time. Because this theory estimates the pace of technology change using the cumulative output or adoption level, the mathematical representation usually follows the S-curve shape. This representation

assumes an upper limit for which the growth of technology or innovation cannot be exceeded. Under this assumption, an analyst can determine the current and the future level of any technology, as well as the time it might take to achieve the saturation level using S-curve growth models (Ryu & Byeon, 2011).

As depicted in Figure 6.3, most emerging technologies generally grow slowly when influenced by the so-called early adopters (innovators) as shown by point 0α . This might be followed by a rapid growth phase caused by the second group of adopters, the imitators, whose actions were influenced by the innovators (point $\alpha\beta$). Finally, much slower growth is then observed just before the market hits its maturity or saturation points where the point with maximum adopters among a given population is reached (Kraja & Braimllari Spaho, 2019; Lotfi et al., 2014; Michalakelis et al., 2008). The characteristics and properties of S-curve models used for most technological forecasting and diffusion studies resemble those of the family of logistic growth models. Next, I describe the empirical approach based on the logistic growth models.

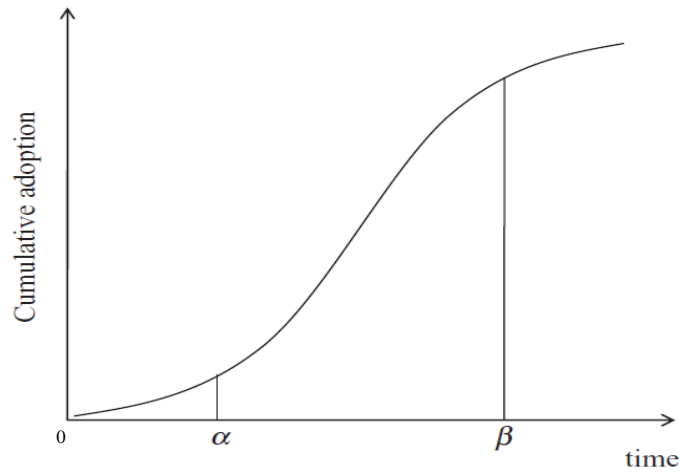


Figure 6.3. S-shaped diffusion curve (Source: Lotfi et al. (2014))

According to Michalakelis et al. (2008), most S-type diffusion models in Figure 6.3 are derived from the differential equation given as follows:

$$\frac{dY(t)}{dt} = \alpha \times Y(t) \times [k - Y(t)] \quad (6.1)$$

Where $Y(t)$ is the total adoption or penetration at time t , α is the diffusion rate, k is the saturation level of the technology, and $(k - Y(t))$ is the fraction of market potential left.

The rest of the diffusion models adopted for this study are derived from the general mathematical representation of the diffusion model expressed in equation (6.1).

6.5.1. The logistic models

Most technological forecasting studies apply the three-parameter logistic model (LM)²⁴. This model describes the growth of technology or innovation within a finite ‘niche population or physically limited resources’. The point of interest then is to describe the trajectories of growth and decline exhibited by the emerging technology, even with limited data. The parameters of the LM expressed in equation (6.2) have been found to adequately capture these trajectories.

$$Y(t) = \frac{k}{1+e^{-\alpha t - \beta}} \Rightarrow \frac{k}{1+e^{-\alpha(t-t_m)}} \quad (6.2)$$

For a computational purpose, equation (6.2) can be expressed as follows:

$$Y(t) = \frac{k}{1+e^{\left[\frac{-\ln(81)}{\Delta t}(t-t_m)\right]}} \quad (6.3)$$

Where $Y(t)$ is the number of growing technologies or total diffusion at time t , k is the feedback which asymptotically causes the growth to slow down or saturate to a niche capacity²⁵, α describes the rate or the steepness of the S-curve (equivalent to $\Delta t = (\ln 81)/\alpha$ in equation (6.3)), and β is the location parameter which specifies the midpoint (t_m) of the growth trajectory at $Y(t_m) = k/2$, that is, the time taken for the curve to reach half of the maximum growth potential k of the diffusing technology.²⁶

Equation (6.2) can be linearised using the Fisher-Pry model if we assume that $F(t) \equiv Y(t)/k$ and substitute for k in equation (6.3). The resulting Fisher-Pry model can be expressed as follows:

$$\frac{F(t)}{1-F(t)} = e^{\frac{-\ln(81)}{\Delta t}(t-t_m)} \quad (6.4)$$

²⁴ This is also referred to as Meyer’s equation (Meyer, 1994).

²⁵ The k parameter of the LM also refers to the carrying capacity of the population. Equation (6.2) reduces to the exponential growth equation when $N(t) \ll k$.

²⁶ β was replaced with t_m in equation (6.2) by defining $\beta = -t_m\alpha$ in equation (6.2). See Meyer (1994). e is the base of a natural logarithms with numerical value equivalent to 2.71828.

Equivalently, it can be expressed in log form as follows, considering equation (6.3).

$$\ln (F(t)) = \frac{-\ln(81)}{\Delta t} (t - t_m) \quad (6.5)$$

The log plot of equation (6.5) on the y-axis produces a straight line that enables the estimation of Δt and t_m . Because the Fisher-Pry curve is normalised by k , it can facilitate the comparison of several logistic growth processes. Bhargava (1995) introduced the generalisation of the Fisher-Pry model by specifying a growth parameter ($B = a + be^{ct}$) to be time-dependent, thereby making it more suitable for forecasting technological substitution²⁷.

The generalisation of the LM in equation (6.2) is the Richard model (RM). Unlike the LM, the RM is a four-parameter model where the righthand denominator is expressed in terms of the shape parameter (δ). The resulting equation is defined as follows:

$$Y(t) = \frac{k}{(1 + \delta \cdot e^{-\alpha(t-t_m)})^{1/\delta}} \quad (6.6)$$

All parameters are as previously defined. The RM reduces to LM if $\delta = 1$.

6.5.2. The Gompertz model

Another growth model commonly used for diffusion studies is the Gompertz model. The mathematical representation of the Gompertz model is expressed as follows:

$$Y(t) = k \cdot e^{-\beta e^{-\alpha t}} \quad (6.7)$$

As with the LM, the Gompertz model also involves the estimation of three parameters. A distinguishable feature this model is that the diffusion is slower at the start and the endpoint of the saturation but very rapid at the midpoint, making it a suitable model for characterisation of some emerging technologies. The parameter β is related to the inflection time when the diffusion process has achieved approximately 37% of its maximum capacity.

Table 6.1 summarises the diffusion models used for this study. As with many diffusion studies, a comparative analysis of these models is carried out to select the most

²⁷ Here, a is constant and b is the substitution rate.

appropriate model for characterising the diffusion of financial technologies (electronic payment platforms) in Nigeria.

Table 6.1. Summary of diffusion models used in this study

S/No	LM	Gompertz model	Richard model
equation	$Y(t) = \frac{k}{1 + e^{-\alpha t - \beta}}$	$Y(t) = k \cdot e^{-\beta e^{-\alpha t}}$	$Y(t) = \frac{k}{(1 + \delta \cdot e^{-\alpha(t-t_m)})^{1/\delta}}$
Parameter	α	Diffusion rate	Diffusion rate
	β	Related to inflexion point, as $\beta = -t_m \alpha$	Related to inflexion point $\beta = -t_m \alpha$
	k	Carrying capacity	Carrying capacity
	δ		Shape parameter
Application	Ecological/biological prediction of bacterial growth, plant growth, and fish/animal weight. Technology forecasting and diffusion of mobile phones adoption, etc.	Ecological/biological prediction of bacterial growth, plant growth, and fish/animal weight. Technology forecasting and diffusion of mobile phones adoption, etc.	Ecological/biological prediction of bacterial growth, and plant growth, fish/animal weight. Technology forecasting and diffusion of mobile phones adoption, etc.

Source: Authors.

6.6. Data construction and description

To study the dynamics of the diffusion process of the EPS, I construct two datasets: data on supporting infrastructure and data on payment related transactions (Table 2). For the supporting infrastructure in Panel A, diffusion is measured by either subscription per a fraction of the population (as in the case of mobile/internet subscription) or the number of self-service banking technology installed per a fraction of the population (as in the case of ATM).

Unlike the supporting infrastructure, however, the unit measure of adoption/diffusion of the electronic payment technologies in our sample has not been classified. Furthermore, available data does not provide the number of individuals who adopted these technologies.

Nevertheless, a choice must be made between the *volume* and the *value of financial transactions* using these technologies, or the proportion (%) of the later or the former as proxies of the adoption level²⁸. I opt for the *volume of transactions* as a proxy for measuring the adoption/diffusion of these technologies because in the absence of a direct measure, it fairly demonstrates the number of times individuals and firms utilised these technologies as channels for financial exchange. Moreover, the *value of financial transactions* will skew the adoption/diffusion rate in favour of technologies with a higher amount per single transaction. Therefore, as demonstrated in panel B of Table 2, the *volume of financial transactions* using each technology is used as the measure of the adoption/diffusion. It then follows that in the technology substitution section, the share of the *volume of financial transactions* for each technology will be estimated and used.

As a prelude, I begin by examining the diffusion of three supporting infrastructure, namely mobile subscription, internet penetration, and the number of installed ATM. These, in my opinion, facilitated the adoption of the financial technologies.

Table 6.2. Data and variable description²⁹

Panel A: Supporting infrastructure			
Variable	Symbol	Description	Data Source
Mobile Subscription	<i>Mbcs</i>	Mobile subscription per 100 people	World Bank and ITU
Internet access	<i>Indui</i>	Individual using internet as % of population	World Bank and ITU
ATM installed	<i>ATMi</i>	No. of ATMs installed per 100,000 adults	World Bank and CBN
Panel B: Digital financial payment systems			
ATM Vol.	<i>ATMv</i>	Volume of financial transactions using ATM	CBN
Web Vol.	<i>Webv</i>	Volume of financial transactions using Web	CBN
Mobile Vol.	<i>Mobv</i>	Volume of financial transactions using mobile	CBN
POS Vol.	<i>POSv</i>	Volume of financial transactions using POS	CBN

Source: Authors.

²⁸ Volume and value of financial transactions are defined as the number of electronic payment related services transmitted between two economic agents and the value of such transaction, respectively.

²⁹ Data are downloadable from; <https://data.worldbank.org/indicator/IT.CEL.SETS.P2>, <https://www.itu.int/en/ITU-D/Statistics/Pages/default.aspx>, and <http://statistics.cbn.gov.ng/cbn-onlinestats/Default.aspx>

6.7. Data analyses and results

6.7.1. Digital supporting infrastructure

This study identifies three digital supporting infrastructures instrumental to the growth and diffusion of electronic payment technologies in Nigeria. The first panel of Figure 4 shows the trend in mobile subscription per 100 people, internet subscription as a percentage of the population, and installed ATMs per 100,000 people. The diffusion rate of mobile subscriptions increases rapidly from 0.0245% in 2000 to approximately 55% in 2010, diffusing at approximately 5.5% annually in the first decade. Furthermore, a diffusion rate of approximately 33% was achieved between 2010 and 2018, comprising a total of 88% diffusion rate of mobile telephony in Nigeria per 100 people by 2018. The result also shows that internet penetration grew rapidly from 0.0641% in 2000 to 11.5% in 2010 and 42% in 2017. Taken together, the diffusion rate of internet users in Nigeria was at 2.5% per annum between 2000 and 2017. Both results show growth trajectories that suggest closing digital divides. Meanwhile, ATMs installed per 100,000 adults also rose from 0.68% in 2005 to approximately 17% in 2018.

The diffusion of these digital supporting infrastructure was a catalyst that facilitated the rapid growth and development in the digital financial technologies seen in Nigeria within the last decade. As argued earlier, among the most popular emerging digital financial technologies, especially payment systems that have been introduced following these enabling infrastructure, are ATM, POS, Web, and Mobile payment. My objective, therefore, is to forecast the future trajectories of the volume of transactions using these digital payment technologies.

The second panel of Figure 6.4 shows the diffusion of these digital financial payment systems expressed in terms of the *volume of financial transactions*. The first sub-figures show rapid growth in the *volume of financial transactions* using ATM and mobile payments. Similarly, there was also slow but steady growth in the *volume of financial transactions* using POS and Web, especially from 2013 onward. In general, it can be argued that irrespective of technology, the trends show rapid growth in the *volume of financial transactions*. Next, I forecast the diffusion of these technologies using the diffusion models evaluated above, including the logistic substitution model.

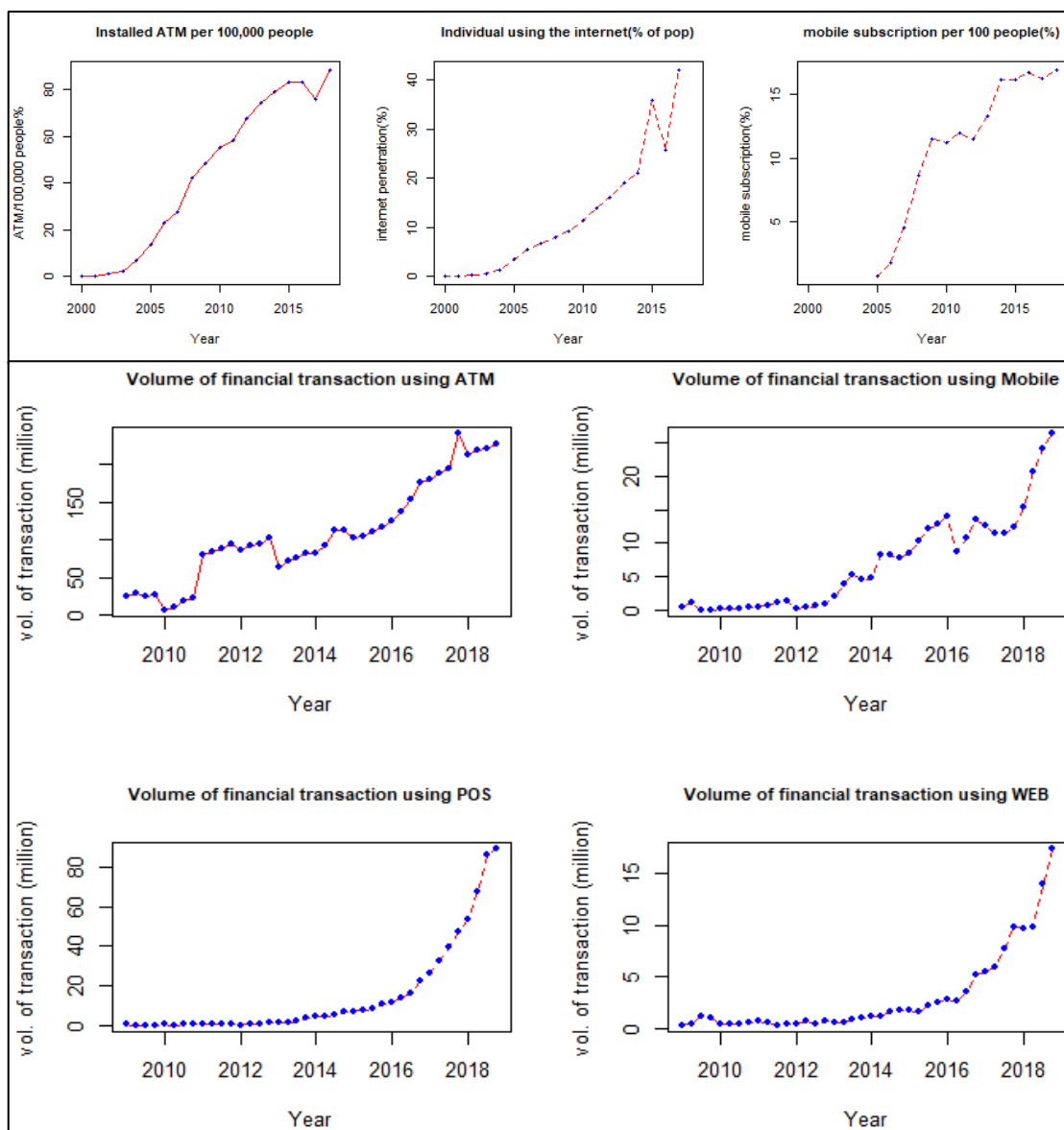


Figure 6.4. Digital supporting infrastructure in Nigeria (Source: authors).

6.8. Estimation results

The estimated parameters of the diffusion models and goodness of fit statistics for the forecasts are presented in Panel A of Table 6.3. First, a choice must be made about the diffusion model appropriate for forecasting these financial technologies³⁰. A test between logistic and Gompertz models (found on Panel B of Table 6.3) shows that LM is appropriate for forecasting the diffusion of ATM, POS, and web payment systems, whereas the Gompertz model is appropriate for forecasting the adoption of the mobile platform³¹. This result agrees with empirical research that showed that different diffusion models are suitable for different technology forecasts. This is because factors such as the initial number of subscribers, features of the innovation (including price, ease of use, and availability), and sometimes, state policy regarding the innovation affect the technology's performance.

The forecast for the volume of financial transactions using ATM based on logistic family models shows that cumulative adoption will peak between 6,144 and 6,574 million transactions. This peak (market saturation) in the cumulative volume of financial transactions using ATM is estimated to occur in 2027. The result also shows that half of the market potential has been saturated between 2017 and 2018. For cumulative adoption using the POS, the result shows a peak of between 2,087 and 2,144 million cumulative volume of transactions between 2024 and 2026, half of which will be achieved in 2020. The cumulative transactions using WEB is estimated to peak between 431 and 484 million transactions in 2026. Approximately half of this was achieved in 2018.

For the mobile payment systems, the cumulative transactions (adoption) are estimated to peak in 2040 with approximately 434 million transactions, half of which was expected to peak in 2020³².

Figures 6.5 and 6.6 show the fitted and the forecasted value with 95% confidence levels, the linear transformation using Fisher-Pry, and the rate of change for each set of

³⁰ As noted in earlier, the RM reduces to LM if $\delta = 1$. For all financial technologies, $\delta = 1$. Hence, both models provide important information about the forecast and are not significantly different in parameter estimation.

³¹ This test is based on the research of Martino (2003).

³² The model building procedure involves setting several initial parameters of the nonlinear models. Therefore, results in Table 6.3 are the best fits among several alternatives found during the convergence of the nonlinear estimation procedure using lab4 (<https://logletlab.com/>).

technologies: ATM and POS, and Mobile and Web, respectively. First, as shown by the adjusted R-square, the fitted curves mimic or explain the variations in the datasets between 94% to 98% of the time. Second, the forecast perfectly falls within the 95% confidence band for all models evaluated. To ensure robust confidence bands, I use bootstrapping with approximately 400 Monte Carlo iterations. Lastly, in addition to the acceptable level of other fitting errors (MAPE and MAD) in Table 6.3, the graph of the estimation errors against time also suggest that the models adequately fit the data and are appropriate for forecasting (See appendix 6C). These results are, however, subject to the assumption that deviations in other factors remain at least as minimal as they are during the data period. Next, I forecast the market share of these EPSs using the logistic substitution model.

Table 6.3. Estimated growth model for four digital financial technologies in Nigeria.

Panel A: Estimated Models																	
Fintech	Model	d	K	a	tm	α	SSE	RMS	MAD	MAPE	AICc	Ad-R2	p	10%	50%	90%	99%
ATM	<i>Logistic</i>	1.380	6144	9.690	2017	0.453	482167	110.00	99.900	0.179	499	0.956	0.000	2012	2017	2022	2027
	<i>Richards</i>	2.920	6574	1.210	2018	0.480	461658	107.00	96.400	0.186	499	0.941	0.000	2012	2018	2022	2027
	Gompertz	6.400	12612	9.530	2019	0.155	307385	92.40	81.300	0.100	437	0.988	0.000	2014	2019	2034	2048
POS	<i>Logistic</i>	0.185	2144	5.310	2020	0.828	1147	7.98	7.380	0.105	137	0.996	0.000	2017	2020	2023	2026
	<i>Richards</i>	0.159	2087	1.670	2020	1.260	428	4.88	4.410	0.069	123	0.998	0.000	2017	2020	2022	2024
	Gompertz	0.179	2050	4.320	2020	0.343	6611	21.70	18.900	0.169	138	0.973	0.000	2017	2020	2026	2033
Mobile	<i>Logistic</i>	0.249	425	7.500	2021	0.586	251	3.17	2.850	0.191	139	0.984	0.000	2017	2021	2024	2028
	<i>Richards</i>	0.208	397	1.770	2020	0.934	168	2.54	2.290	0.164	135	0.988	0.000	2017	2020	2023	2025
	Gompertz	0.205	434	6.480	2020	0.229	652	5.71	4.690	0.207	137	0.956	0.000	2017	2020	2030	2040
WEB	<i>Logistic</i>	0.221	431	7.430	2018	0.592	1474	6.49	5.610	0.222	240	0.993	0.000	2014	2018	2022	2026
	<i>Richards</i>	0.362	484	0.940	2018	0.584	1543	6.94	5.990	0.170	227	0.989	0.000	2015	2018	2022	2026
	Gompertz	0.229	853	6.900	2019	0.215	635	5.04	4.000	0.068	162	0.996	0.000	2016	2019	2030	2040
Panel B: Model selection (choosing between Gompertz and Logistic)																	
						IncvATM		IncvPOS		IncvMOB		IncvWEB					
_t						-0.1147***		-0.0576**		0.0267		-0.1653***					
						(0.0310)		(0.0260)		(0.0597)		(0.0385)					
_t2						0.0017***		0.0012**		-0.0010		0.0037***					
						(0.0006)		(0.0006)		(0.0012)		(0.0008)					
_cons						-0.8515**		-1.1668***		-2.0328***		-0.7671*					
						(0.3704)		(0.2564)		(0.6268)		(0.4196)					
Obs.						39		39		39		39					
R-squared						0.6764		0.1481		0.1286		0.5400					

Standard errors are in parenthesis.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

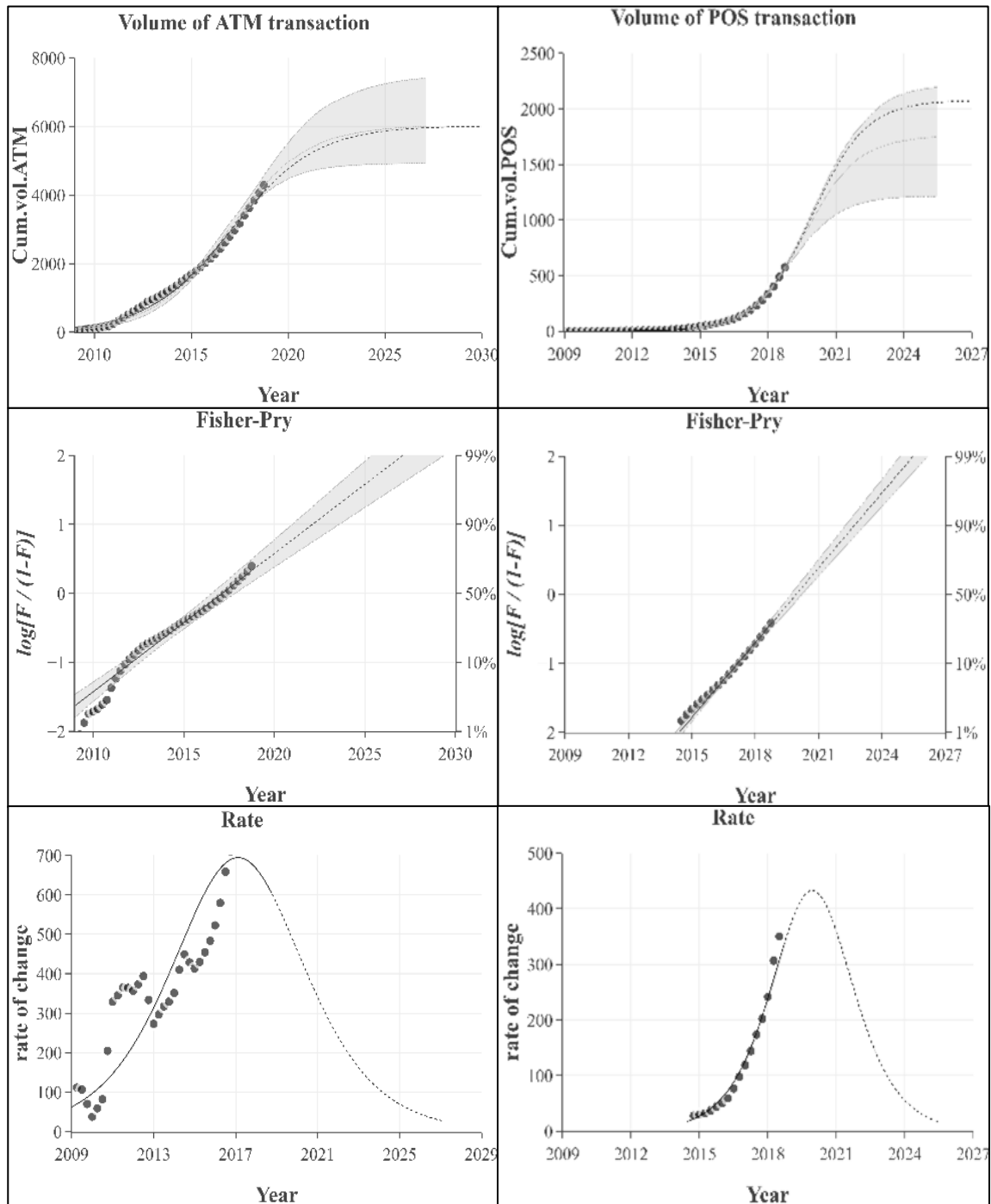


Figure 6.5. Forecasts for the cumulative volume of payments transacted via ATM and POS (Source: estimated from data using lab4).

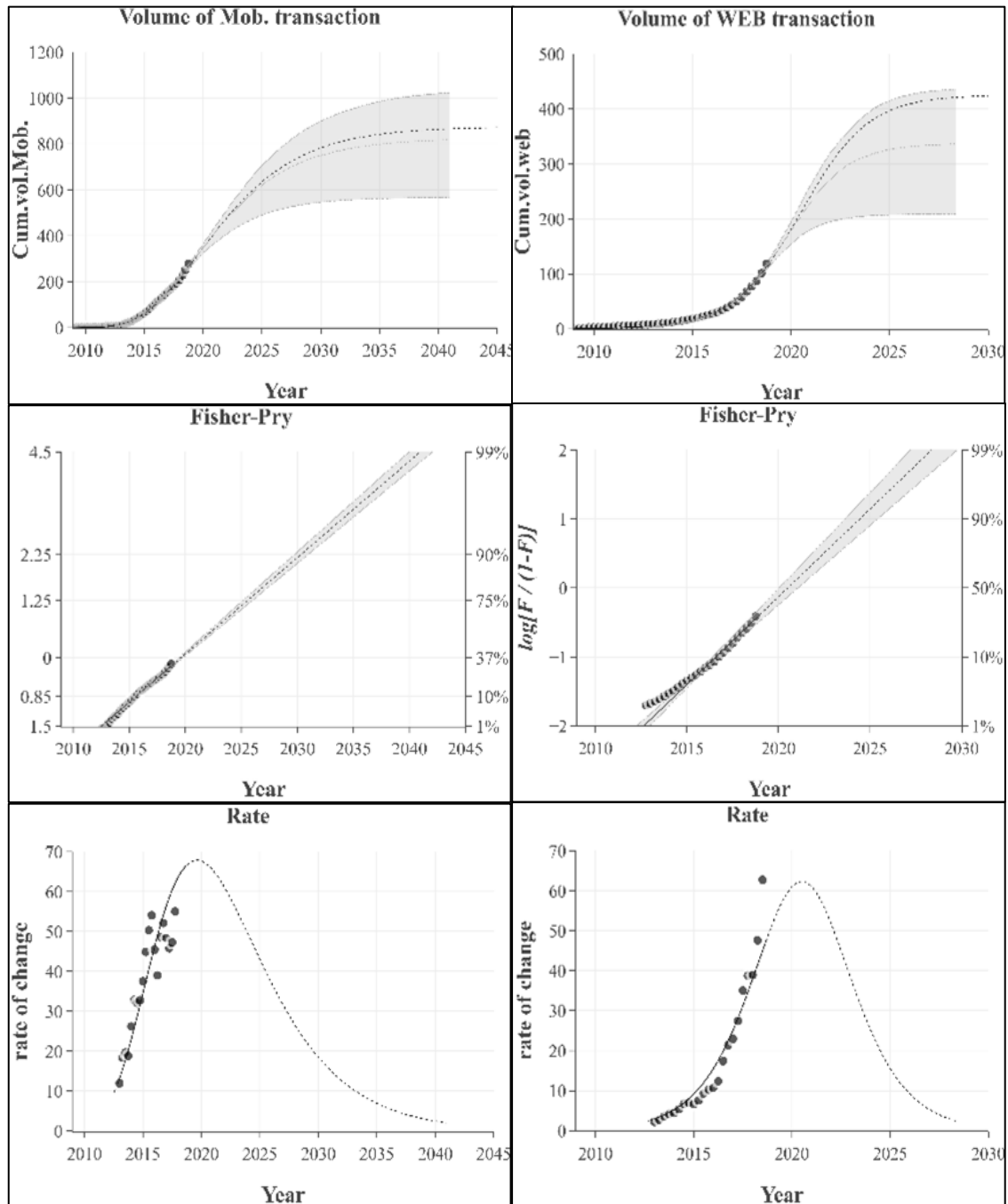


Figure 6.6. Forecasts for the cumulative volume of payments transacted via Mobile and Web (Source: estimated from data using lab4).

6.9. Logistic substitution model

In this subsection, I evaluate how these technologies compete in the payment systems niche market in terms of the volume of payments transacted. These technologies do have different features, provide different yet interconnected and overlapping financial services, and are therefore not perfect substitutes. Nevertheless, it can be argued that the proxy for the adoption of these technologies (the volume of financial payments transacted) allows one to evaluate how they compete in the financial payments market. I apply logistic substitution techniques and use graphical illustration to show the competition and the saturation point of the volume of payment transactions for these technologies (Figures 6.7).

The first panel of Figure 6.7 shows the fraction of the market share of the volume of payment transacted using each payment technologies scaled to unity. It shows S-curve diffusion pattern typical of logistic or Gompertz function, as demonstrated earlier³³. The second panel of Figure 6.7 shows the Fisher-Pry transformation. Several meaningful inferences emerge from this figure.

First, the market share of the volume of transactions using ATM decreases to a tail-end between 2025 and 2030. Second, the result for POS shows a turning point between 2025 and 2030. Third, the market share of the volume of payments using the mobile payment system is projected to rise into the future and possibly dominate the future market share in terms of payment-related transactions. These results agree with our earlier estimates. For example, estimates suggest that the cumulative adoption of ATM payments would peak in 2027, while that of mobile payments will peak in 2040. The deviations between the data and the forecast on Figure 6.7 seem apparent, which is typical of emerging technologies with limited data. Nevertheless, these results appear to support earlier findings of this research. Therefore, they provide ample empirical evidence on the future trajectories of these payment platforms.

³³ LSM uses the actual number of adoptions, calculated as the market share of each technology. LSM could reveal a bell shape with different quadrants depending on the lifecycle of the technology, as shown by Figure 6 (courtesy LSM II, IIASA).

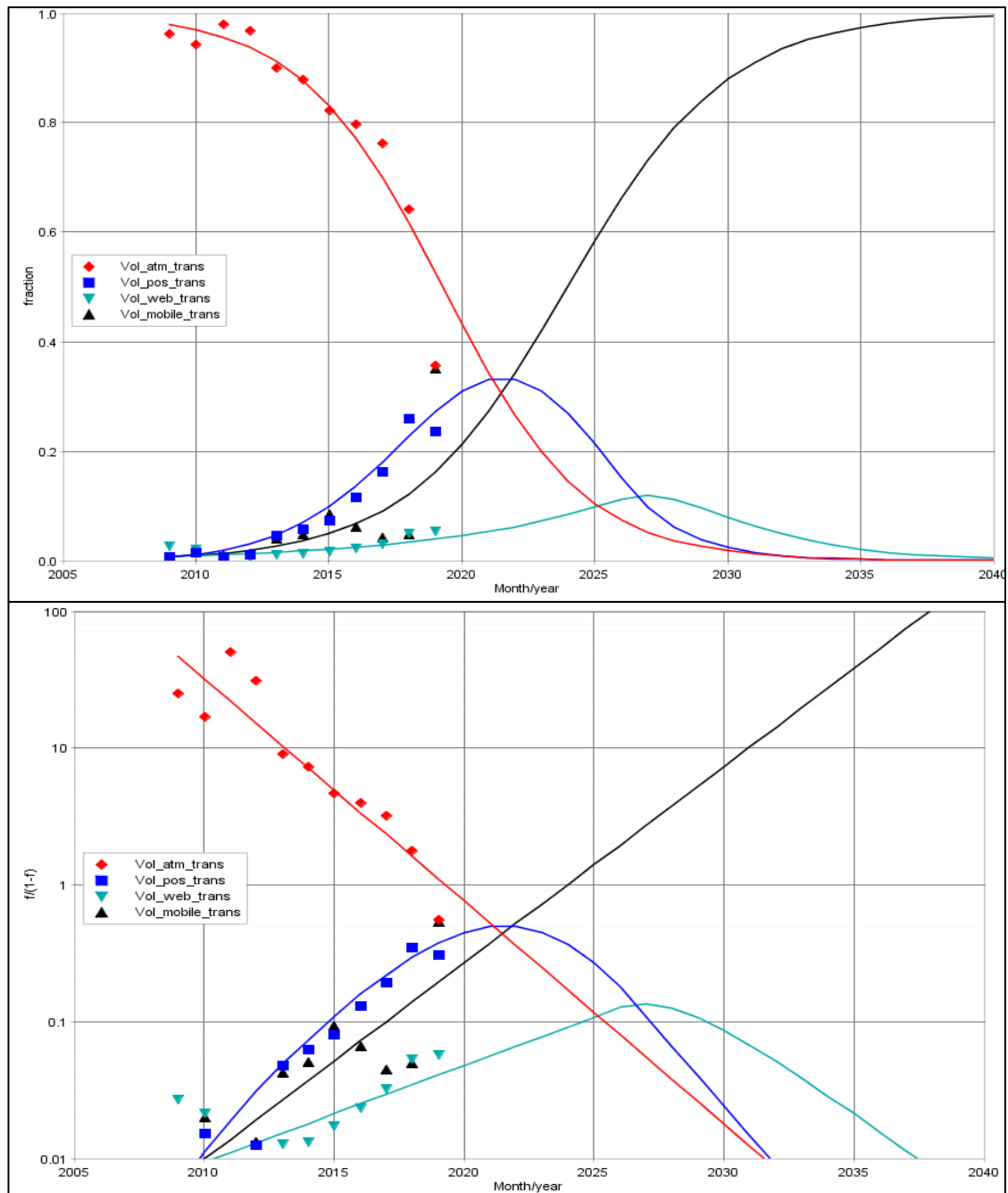


Figure 6.7. Logistic substitution model for the market share of electronic payments in Nigeria (Source: estimated from data using LSM II).

6.10. Discussion and conclusion

6.10.1. Discussion

The introduction and diffusion of financial technologies enable financial institutions in Nigeria and beyond to remotely provide electronic banking services. One such important electronic banking service is electronic payments. This research evaluates the four most important EPSs in Nigeria: ATM, POS, mobile, and Web payments. I use data on the volume of financial payments transacted as proxies for the adoption of these technologies.

The diffusion of ATM, POS, and web payments measured by the volume of financial payments transacted is forecasted to last between 2025 and 2030, and considerably decline thereafter. However, the diffusion of the mobile payment systems measured by the volume of financial payment transacted is forecasted to last several years into the future (2040 and beyond). These findings are important to policymakers and managers, especially those in the financial ecosystem.

The future decline in the adoption of ATM and POS payments is arguably connected with the features and size of these technologies. These technologies offer limited payment options built around their features and functions. Moreover, payment transactions on these platforms require physical contact with these limited technologies which are either owned by financial institutions, business units, or very few individuals. Meanwhile, web payments are those payments initiated through internet-enabled computers. However, with the introduction of smaller digital devices, the use of Web payments will be disruptive in the future.

As noted in the literature, the saturation or carrying capacity of technologies or innovations could arguably be dynamic. It could change from one pulse to another (Meyer & Ausubel, 1999). Therefore, the forecasted decline in the volume of payments on these technologies may not imply discontinuation (adoption). Newer compatible payment products in the future could alter the carrying capacities of these technologies.

The mobile payment system has been identified as an innovation that has disrupted payment systems in Europe, Asia, and the United States of America. The success of this disruptive service innovation in China was recently documented (Li & Li, 2020). As one

of the many service innovations built and transmitted using mobile telephony, its usefulness and rapid diffusion have been anticipated. For example, the CBN in 2010 identified the mobile channel as a means to drive financial inclusion, given the large unbanked population who are either using or are more likely to use mobile phones in the future. Following this recognition, the apex bank created a scheme for the introduction and management of mobile payments in Nigeria. The rationale is simple: with strong and secure mobile payment systems in place, access to mobile phones could mean access to financial services. Moreover, mobile payment has made person to person, person to business, and business to business payments safe, easy, and convenient.

The mobile payment system has also been identified as the bedrock of e-commerce. For example, to resolve the trust crises in e-commerce in 2003, an e-commerce giant, Alibaba introduced a mobile payment system, Alipay. This initiative was so successful that it became the largest payment platform in China (Li & Li, 2020).

As a fast-growing and emerging market economy with expanding financial sector, the Nigerian payments market is also growing and offers excellent potential for economic development. As this study demonstrates, the mobile payment system in Nigeria is developing and has the potential to dominate the payments market going forward. Therefore, this system promises to be an excellent tool for a sustainable cashless economy and financial inclusion. However, like many financial service innovations in developing countries, trust, poor digital security infrastructure, and weak policy implementation have shaped, and will continue to shape, the future trajectories of mobile payment products. Therefore, the successful diffusion of this innovation over its lifecycle depends on consumer perception and on the commitment of policymakers, managers, and regulators to ensure a sustainable, secure, and efficient mobile payment systems.

6.10.2. Conclusion

This study provides two important outcomes. On the one hand, I show that the diffusion of electronic payments in the context of Nigeria financial payments system can be adequately modelled using S-curve diffusion models. In our case, the Gompertz and the logistic family models are appropriate for forecasting the diffusion of these payment systems. More specifically, the logistic function is found to be appropriate for forecasting

the diffusion of ATM, POS, and Web payments, whereas, the Gompertz model is suitable for forecasting the diffusion of the mobile payment system. This finding is important for characterising the diffusion of similar payment systems in Nigeria, and perhaps, other developing countries.

On the other hand, this study provides empirical evidence on the possible disruption of the payment systems in our sample. First, within the four EPSs evaluated, the mobile payment system is forecasted to emerge as the most diffused payment technology given the volume of financial exchange that will occur on this platform. Second, the ATM, POS, and the Web payments will witness decreasing adoption given the volume of financial payment transactions on these platforms.

Appendix 6A

Supporting infrastructure

Year	Mobile Subscription	Internet Subscription	ATM per 100,000 pop
2000	0.02	0.06	
2001	0.21	0.09	
2002	1.22	0.32	
2003	2.39	0.56	
2004	6.76	1.29	
2005	13.38	3.55	0.68
2006	22.68	5.55	1.78
2007	27.60	6.77	4.48
2008	41.92	8.00	8.64
2009	48.29	9.30	11.46
2010	55.08	11.50	11.22
2011	58.45	13.80	11.94
2012	67.44	16.10	11.49
2013	74.08	19.10	13.31
2014	78.77	21.00	16.18
2015	83.27	36.00	16.21
2016	83.00	25.67	16.73
2017	75.92	42.00	16.32
2018	88.18		16.92

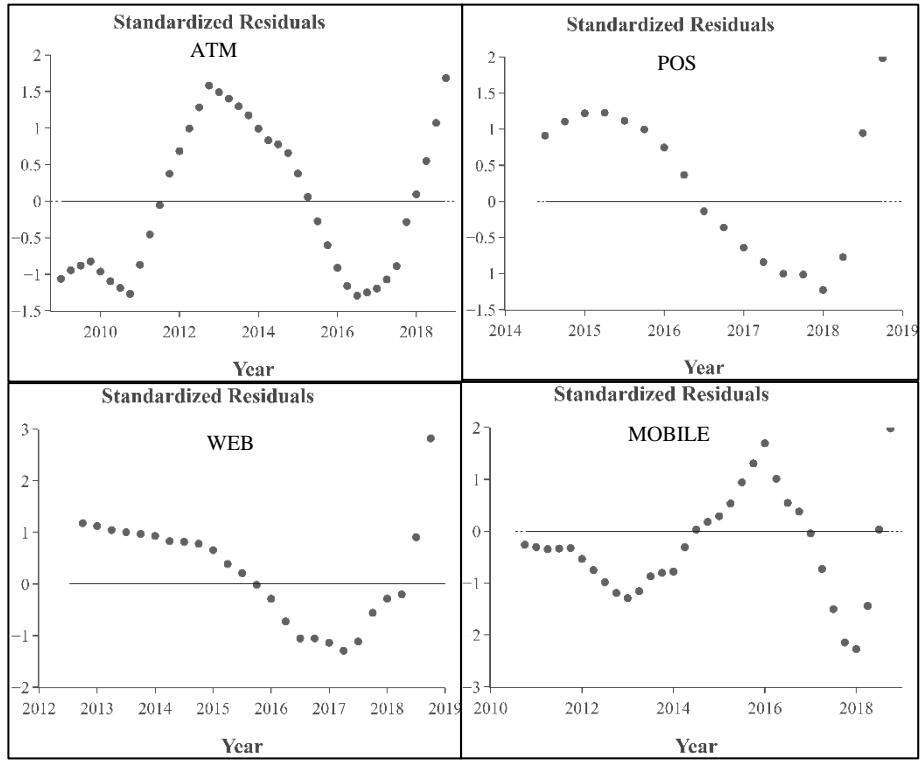
Appendix 6B

Summary statistics of the payment technologies

Year	Tech	mean	sd	min	max	Year	Tech	mean	sd	min	max
2009	vatm	27.290	1.908	25.725	29.947	2014	vatm	100.026	14.736	82.803	112.400
	vpos	0.230	0.019	0.210	0.252		vpos	5.204	1.058	4.359	6.717
	vweb	0.676	0.420	0.303	1.143		vweb	1.397	0.332	1.108	1.759
	vmobp	0.452	0.461	0.110	1.093		vmobp	7.289	1.615	4.879	8.228
2010	vatm	15.033	6.795	7.763	22.729	2015	vatm	108.397	6.601	101.872	116.870
	vpos	0.268	0.039	0.237	0.325		vpos	8.430	1.387	7.210	10.372
	vweb	0.400	0.076	0.332	0.502		vweb	1.995	0.399	1.580	2.436
	vmobp	0.289	0.113	0.170	0.436		vmobp	10.983	1.996	8.526	12.954
2011	vatm	86.892	6.501	79.612	95.277	2016	vatm	147.560	22.191	124.790	175.891
	vpos	0.525	0.147	0.384	0.701		vpos	15.929	4.626	11.746	22.350
	vweb	0.483	0.160	0.289	0.670		vweb	3.522	1.170	2.658	5.175
	vmobp	0.912	0.375	0.518	1.311		vmobp	11.763	2.504	8.644	14.092
2012	vatm	93.872	6.408	86.690	102.000	2017	vatm	200.137	27.090	178.965	239.692
	vpos	0.639	0.450	0.119	1.183		vpos	36.567	8.956	26.647	47.535
	vweb	0.569	0.181	0.374	0.724		vweb	7.248	1.924	5.520	9.740
	vmobp	0.574	0.362	0.212	1.059		vmobp	11.951	0.588	11.363	12.610
2013	vatm	73.823	7.279	64.819	81.927	2018	vatm	218.880	5.469	212.371	225.460
	vpos	2.351	0.996	1.435	3.685		vpos	73.973	16.685	53.563	89.059
	vweb	0.725	0.210	0.533	0.981		vweb	12.704	3.703	9.634	17.382
	vmobp	3.953	1.369	2.093	5.309		vmobp	21.557	4.784	15.253	26.247

Appendix 6C

Forecast errors



Chapter 7

Technological Learning in the Nigerian Financial System II

~ The diffusion of electronic banking in Nigeria (a survey) ~

7.1. Introduction

This chapter evaluates the diffusion of electronic banking among a large sample of respondents using data generated from a field survey. The chapter addresses the following research questions: (1) What is the diffusion level (gain) of electronic banking in Nigeria in recent time? (2) What are the major challenges of electronic banking diffusion in Nigeria (especially among small business owners)? (3) What are the socioeconomic determinants of electronic banking adoption in Nigeria? To answer these research questions, this chapter employs Generalised Structural Equation Modelling (GSEM).

7.2. Background of the study

As the digital divide narrows in Nigeria, digital ecosystems have been created, providing opportunities to individuals and businesses to perform any kind of bank transactions by a mere ‘click’ on digital devices. The results of such have been lower transaction costs, and accelerated business and economic growth, especially for developing economies like Nigeria (Avilés et al., 2016; Fife & Pereira, 2016). With internet and mobile penetration estimated at 42% and between 65-70% in 2017, respectively, Nigeria has become Africa’s largest market not only in digital mobile telecommunication but also in other digital ecosystems associated with the emergence of mobile technologies (Gillwald et al., 2018; ITU, 2019). According to GSM’s intelligence report of 2019, of the 62 million new mobile subscribers forecasted for 2020, 32 million subscribers will come from Nigeria, higher than all other countries in Sub-Sahara Africa put together (GSM, 2019). The wave of these digital mobile technologies and other financial technologies brings numerous digital electronic banking services, enabling the so-called branchless banking in Nigeria. In addition, some policy reforms from the CBN in 2018, such as granting licences to Payment of Service Banks (PSBs), have allowed mobile operators to offer digital financial services. This has increased the penetration of mobile money services (CBN, 2018b; GSM, 2019).

As demonstrated in Chapter 2, the Nigerian digital financial system has generated interests among researchers and policymakers in terms of the opportunities, economic benefits, and the challenges it poses, both from demand and supply side along with the regulatory front. However, there exist some gaps. First, given the interdependent and relatedness of e-banking services, there is need to jointly study electronic banking defined in terms of digital financial ecosystems or the various e-banking channels, platforms, and services in use by consumers. Second, studies on the diffusion of electronic banking in Nigeria are limited by scope (sample size and geographical coverage) and do not provide a full view of the issues analysed. Lastly, studies on determinants of electronic banking on a large sample of individuals and small-scale businesses in Nigeria have not been undertaken. These gaps can be summarised into two working objectives: (1) To evaluate the diffusion level, usage, and challenges of the various electronic banking platforms and services in Nigeria, and (2) To analyse the relationship between users' socioeconomic characteristics, and the electronic banking platforms and services adopted.

7.3. Research method

Most technology adoption studies in the field of information sciences rely on one or more of several theories to explain users' intention to adopt a technology or service. Unlike these studies, this chapter formulates a novel approach to measure the relationship between users' physical characteristics and the propensity to adopt at least one of several electronic banking channels platforms and services in Nigeria³⁴. I calibrate users' physical and socioeconomic characteristics in a manner that allows me to construct relationships between these individual characteristics and the propensity to adopt electronic banking in Nigeria (see Table I, panel B), and thereafter apply structural equation modelling (SEM). This enables us to match users' socioeconomic and demographic characteristics to the probability of adopting a given e-banking platform/service. However, to estimate the gains and challenges of e-banking, I utilise the frequency ratios. This approach is useful in empirical survey studies where analysts are interested in knowing the proportion and the average number of people adopting (using) technologies (services).

³⁴ Theories such as Technology Acceptance Model (TAM), Theory of Planned Behaviour (TPB), Diffusion of Innovations (DOI), Technology-Organization-Environment (TOE), or the Unified Theory of Acceptance and Use of Technology (UTAUT) Model are often used to explain users' intention or motivation to adopt or use a new technology or service.

7.3.1. Structural Equation Modelling

SEM is a statistical technique used to model complex relationships between multidimensional or multivariate dependent and independent variables. SEM is a convenient statistical analysis framework that incorporates several statistical methods such as factor analysis, discriminant analysis, regression analysis, etc. (Westland, 2015). SEM has been used extensively to understand complex interrelationships among variables based on theoretical constructs represented by latent factors that cannot be easily modelled by traditional data analytic methods.

The art of SEM begins with a theoretical path diagram where the researcher makes assumptions about the characteristics of *a priori* interrelationships among variables measured by constructs or responses in a study. Then, the researcher makes a confirmatory test about the *a priori* assumption rather than an exploratory analysis of the data (Morrison et al., 2017). SEM combines path analysis and confirmatory factor analysis to model the causal relationship between latent and observable variables. In contrast, the path analysis quantifies the relationship among multiple observable variables, while the confirmatory factor analysis extracts and estimates the latent variable (construct) based on the correlated variation of the data set (Fan et al., 2016).

7.3.2. The Generalised Structural Equation Modelling (GSEM)

GSEM is a framework that combines the power of SEM and the Generalised Linear Model (GLM). This makes it possible to model both continuous and discrete variables together in the same latent construct under various probability density and distribution assumptions (Rabe-Hesketh et al., 2004). GSEM also simultaneously models direct and indirect effects of interacting factors, and thus, provides better results in observational studies (Lombardi et al., 2017).

GSEM can be used for modelling binary response, ordered or count data, multilevel data structures, and factor variable notations (Huber, 2013; Stata, 2018). Therefore, this research proposes GSEM as the most appropriate tool for modelling the socioeconomic determinants of electronic banking adoption.

7.3.3. The empirical model

Suppose that the probability that an individual adopts or uses a specific e-banking platform or service is a function of their age, gender, educational attainment, income class, and proximity to banks or self-service banking technologies (ATMs or mobile money outlets). The general model for the probability distribution derived from the generalised linear model equation (7.1) can be expressed in equation (7.2) (Greene, 2012).

$$g\{y|X\} = X\beta \quad (7.1)$$

$$p(y = \omega|X) = \frac{e^{\beta\omega \cdot X_i}}{\sum_{m=1}^M e^{\beta_m \cdot X_i}} \quad (7.2)$$

Where ω is the outcome equivalent to the value of the response variable Y , and β is the linear regression parameters associated with X_i explanatory variables with m outcomes.

Equation (7.2) reduces to a binary (Bernoulli) logistic model if y takes on a binary response (0 and 1), like the case if an individual adopts or does not adopt a specific e-banking platform or service. In binary logistic regressions, probabilities are based on the odds or likelihood of success or failure. Therefore, equation (7.2) can be used to predict the odds of adopting an e-banking platform.

The probability of success (adopting a specific e-banking platform/service) can be expressed as follows (Gujarati, 2004).

$$p(y = 1|X) = \frac{1}{1 + e^{\sum_{i=2}^m \beta_m \cdot x_i}} \quad (7.3)$$

Where $e^{\beta_1 \cdot X_i} = 1$ when $\omega = 1$ in equation (7.2) because all regression coefficients become zero. For simplicity, equation (7.3) can be written as follows:

$$p(y = 1|X) = \frac{1}{1 + e^{Z_i}} = p1 \quad (7.4)$$

Where $Z_i = \sum_{i=2}^m \beta_m \cdot x_i$ and $p1$ is the probability that a respondent adopts a service.

The odds for adopting a specific e-banking platform or service, defined as a ratio of the probability of adopting a particular e-banking platform or service to the probability of not adopting, is expressed as follows:

$$odds = \left(\frac{p1}{1-p1} \right) = \left(\frac{1}{1+e^{z_i}} \right) / \left(1 - \frac{1}{1+e^{z_i}} \right) = e^{z_i} = e^{\sum_{i=2}^m \beta_m \cdot x_i} \quad (7.5)$$

The logit function transforms the above odd ratios to a linear relationship for estimation purposes. Therefore, the logit function of equation (7.5) can be expressed as follows:

$$\ell = \ln \left(\frac{p1}{1-p1} \right) = \ln(e^{\sum_{i=2}^m \beta_m \cdot x_i}) = \beta_0 + \beta_m X_i \quad (7.6)$$

Equation (7.6) is the empirical model for estimating the likelihood of adopting a service in a binary case, that is, success or failure. However, if the variable takes on several unordered responses such as frequently used e-banking platform or service, the generalised logistic function (also known as multinomial logit) can be used to map the path of the relationship between individual socioeconomic characteristics and one of the several e-banking platform or service. This can be achieved using the generalised logistic equation (7.2).

7.3.4. The theoretical model

The theoretical model for this study can be illustrated using a path diagram (Figure 7.1) with three latent variables as follows: An individual user's characteristics (IC), e-banking characteristics such as the digital *devices* owned, e-banking *platforms* adopted, and the e-banking *services* adopted are assumed to be correlated. I assume that e-banking users' IC significantly affects their choice of e-banking types, both in terms of the platform and services adopted, and the digital devices owned. I also assume that platform is correlated with service.

The relationships between these latent variables can implicitly be observed or estimated using observable endogenous or exogenous variables generated by responses. Under the current assumption, *Device*, *Platform*, and *Service* are dependent on IC. Figure 7.1 can be expanded to see the estimable equation level parameters and extended relationships in the structural model, as demonstrated by Figure 7.2. Assuming that the latent IC is captured by age, education (educ), gender (gnder), employment (emp), annual income (ainc), and nearness to physical banks (nbb)³⁵, I propose that these variables are

³⁵ The IC variables are scaled in ascending order to serve as constructs that allow for correlation measurement during the SEM estimation.

determinants of the *Platform* (imap, ussd, mbm, posp, fpf) adopted, the *Service* (ebus, ebft, ebpu, ebwd, ebbs, fsv) adopted, and the *Device* (smt, nsmp, pctop, pos) owned³⁶. Empirically, we can test broad hypotheses on the relationships between these latent variables as follows:

- (1) H1: There is a significant relationship between IC and platforms adopted.
- (2) H2: There is a significant relationship between IC and services adopted.
- (3) H3: There is a significant relationship between platform and services adopted.

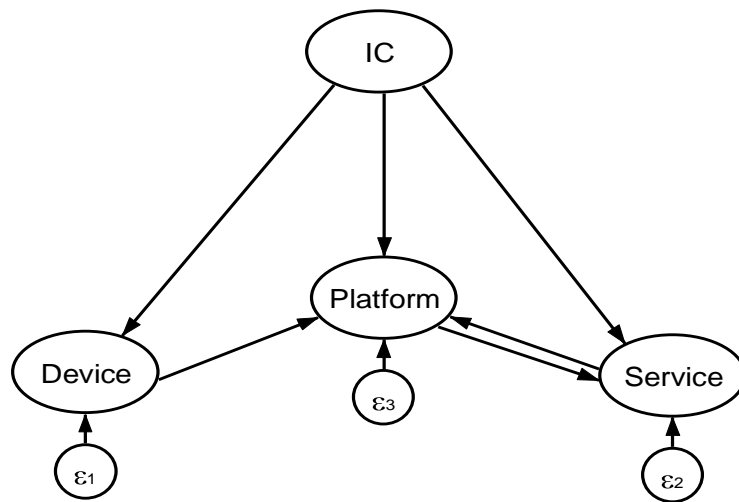


Figure 7.1. Theoretical path diagram

The first hypothesis implies that an individual's economic and social characteristics significantly determine the choices they make about the e-banking platform to adopt. The second hypothesis suggests that an individual's economic and social attributes significantly affect the e-banking service adopted. Finally, the third hypothesis implies that the e-banking service adopted largely depends on the e-banking platform adopted. These hypotheses can be illustrated using SEM path diagram seen on the upper panel of Figure 7.2. One can evaluate the relationship between each sub-variable of IC versus each sub variable of Platform and Service, that is, one could estimate the probability or the odds of an individual with specific ICs adopting a specific e-banking platform or service as demonstrated by the lower panel of Figure 7.2.

³⁶ Refer to Panel B of Table 8.1 for definition of variables.

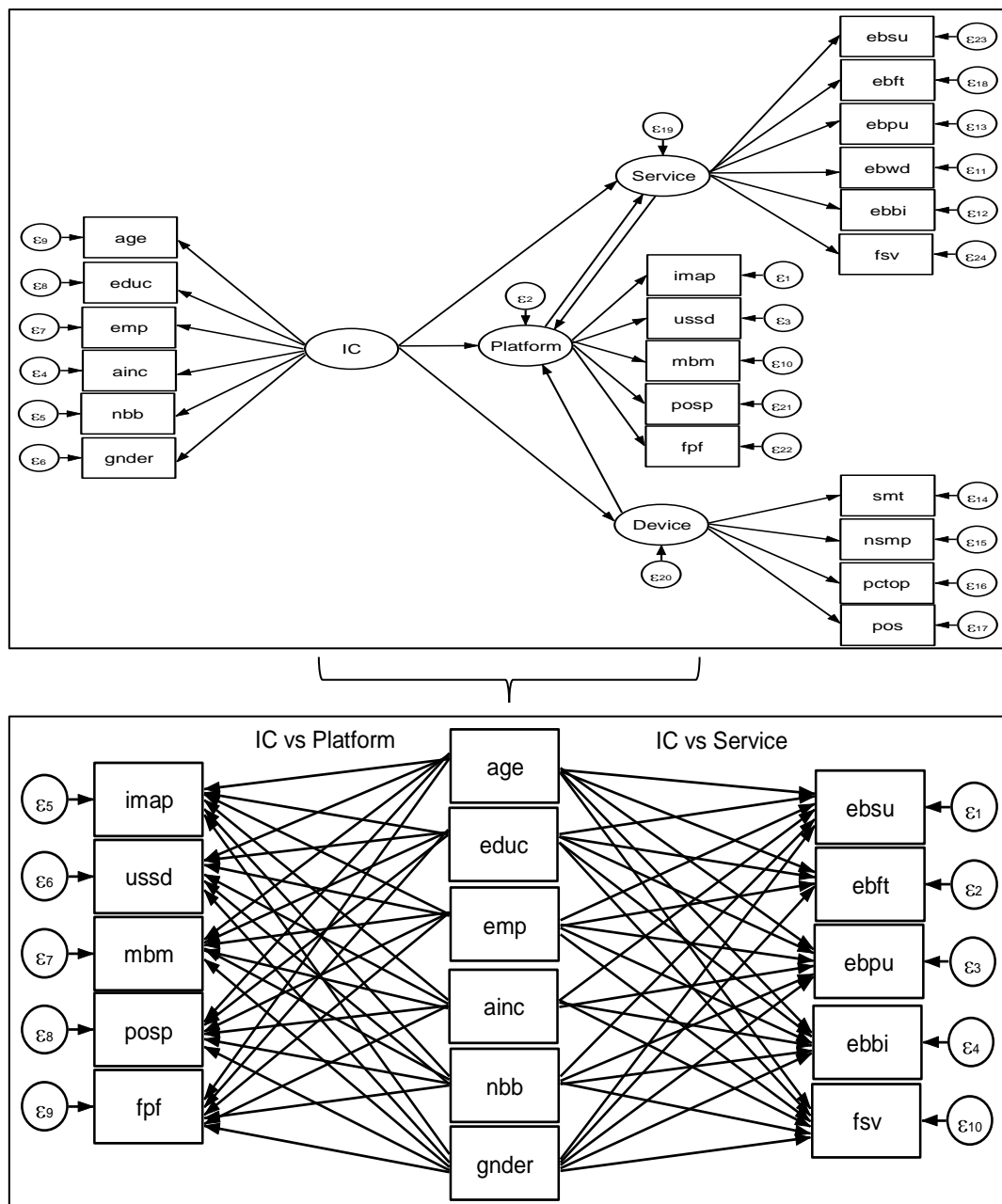


Figure 7.2. Multi-dimensional factor-variable relationship between IC, platform, and service

7.4. Data sampling and the survey procedure

On the survey procedure, this study deploys a structured questionnaire with several sections (see Appendix 7A). Section one evaluates the socioeconomic profile of the respondents. Section two elucidates information on the adoption of e-banking financial technologies, namely digital devices, platforms, and services. Finally, section three evaluates e-banking fraud, theft, and consumer awareness. A total of 11 field enumerators were recruited, trained, and deployed to 11 states drawn from 5 out of the 6 geopolitical zones of Nigeria. We employed the purposive random sampling method, where we carefully evaluate our sampling units to ensure it sufficiently meets our sampling criteria. First, we targeted respondents from all walks of life. Second, due to the study objectives, we purposively targeted approximately 50% of business owners by visiting shopping complexes, market, and business domains. The survey was conducted electronically using DataScope® electronic forms. To achieve this, I coded the instrument into a soft-interactive form which could be administered through a tablet or mobile devices. Field enumerators were then given access to survey forms via user and password enable DataScope® mobile apps (see appendix 7B). Each enumerator administered at least 100 forms for six days and a total of 1128 respondents were sampled between January 2020 to February 2020. Figure 8.3 shows the distribution of sampling units of respondents across the country using the GPS coordinates (figures are the number of respondents interviewed).

Table 7.1. Data and variable description

Panel A: Secondary Data					
	Variable	Symbol	Description	Remark	
IC	age	<i>age</i>	age group of respondents	1~3	
	Gender	Gender	Gender	0-1	
	education	<i>educ</i>	education attainment	1~3	
	employment status	<i>emp</i>	type employment	1~4	
	annual income	<i>ainc</i>	annual income (income level)	1~3	
	proximity to bank branches	<i>nbb</i>	the number of bank branches within...	1~3	
	nearness to ATMs/mobile money	<i>natmm</i>	number of ATM/MM within...	1~3	
	digital devices owned	<i>several</i>	type of digital devices owned, MA (0-NA, 1-AD)	0~1	
	e-banking platforms adopted	<i>several</i>	type of e-banking adopted, MA (0-NA, 1-AD)	0~1	
DD/ PF/ SV	freq. used e-banking platform	<i>several</i>	most frequently used e-banking platform	1~4	
	e-banking service adopted	<i>several</i>	type of e-banking service adopted (MA)	0~1	
	freq. used e-banking serv. adopted	<i>several</i>	most frequently used e-banking service	1~4	
Panel B: Variable definitions					
Symbol	Meaning	Symbol	Meaning	Symbol	Meaning
<i>imap</i>	Internet/mobile apps	<i>ebsu</i>	e-banking subscriptions	<i>smt</i>	Smartphone or tablet
<i>ussd</i>	Fast codes or SMS-banking	<i>ebft</i>	e-banking fund transfer	<i>nsmp</i>	Non-smartphone
<i>mbm</i>	Mobile money	<i>ebpu</i>	e-banking purchase	<i>pctop</i>	Personal computer/laptop
<i>posp</i>	Point sale pay	<i>ebwd</i>	e-banking withdrawal	<i>pos</i>	Point of sale
<i>fpf</i>	Frequently used platform	<i>ebbi</i>	e-banking bills payment		
		<i>fsv</i>	Frequently used service		

MAA - multiple answers allowed, NA - not adopted, AD - adopted.

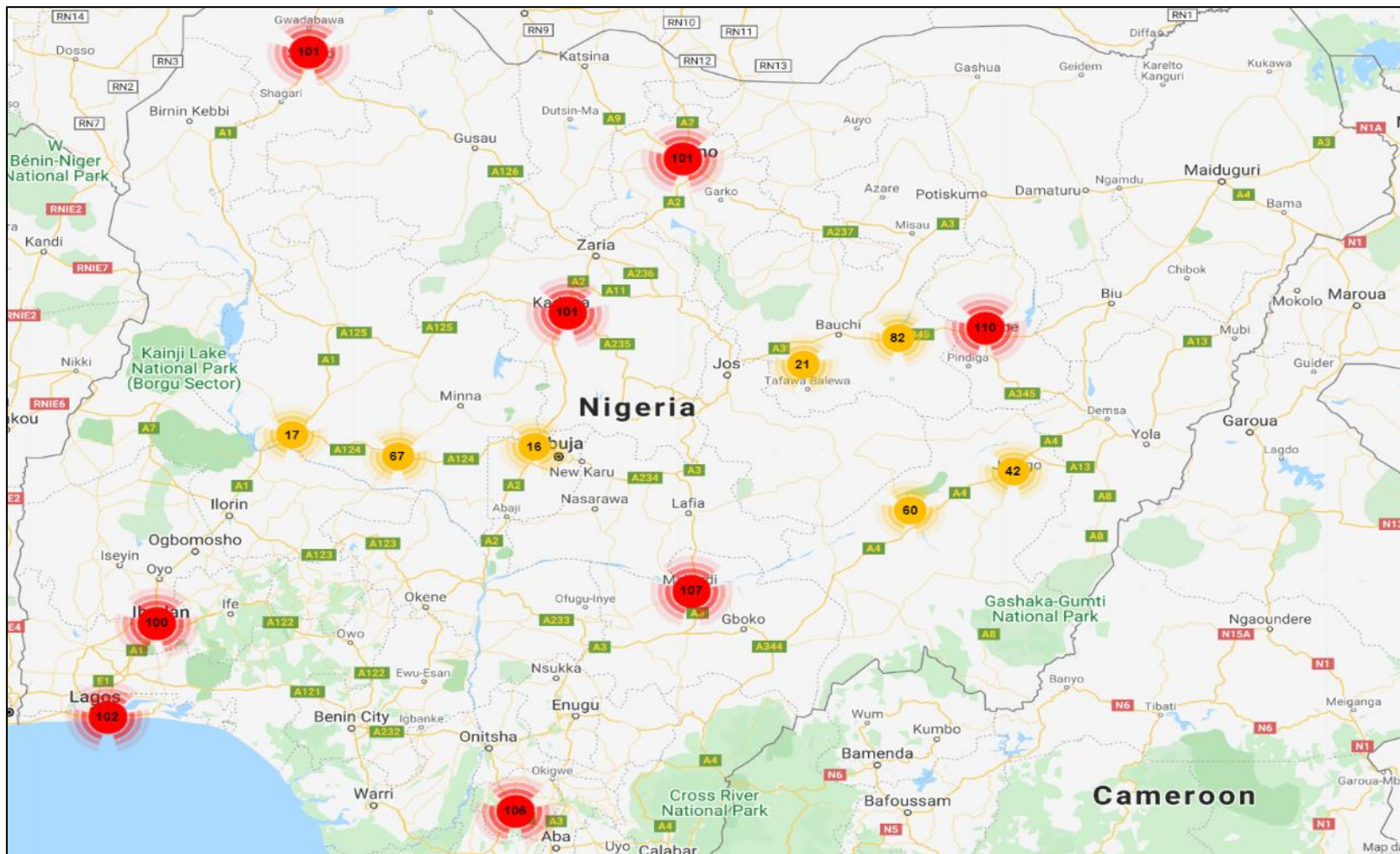


Figure 7.3: GPS coordinates of respondents

7.5. Data analyses and results

7.5.1. The diffusion of electronic banking in Nigeria: Socioeconomic characteristics

A third of the respondents come from rural areas. Approximately 43% are within the ages of 31–40 years and 40% from the low-income category earning less than a thousand dollars annually. In terms of employment and education attainment, 60% of all respondents are informally employed (or self-employed) and have post-secondary education, respectively, implying that these individuals possess reading and writing abilities.

In terms of financial access, Panel B of Table 7.2a shows that approximately 45% and 55% of respondents have a bank branch accessible within a kilometre distance in the case of rural and urban dwellers, respectively. Furthermore, 62% and 65% of the respective respondents have an ATM or registered mobile money outlets within a kilometre from their business location or home. The high financial access in the case of rural dwellers is expected since our samples are drawn from small business units and markets where most banks are clustered to enable traders to make financial transactions with ease. Additionally, the result also suggests that ATM and mobile money operators have increased their presence in rural areas, especially in market or business clusters. On the contrary, more than a third of respondents indicated that accessing a bank branch or ATM or mobile money operators could take more than a two kilometer distance from their regular point of business or home.

On the adoption of electronic banking, the results in Table 7.2b show that 95% of all respondents have used at least one form of electronic banking from internet banking, SMS banking, mobile money banking, and POS banking. Most respondents own readily available digital devices such as smartphones or tablets, non-smartphones, personal computers, and POS, which they deploy for e-banking. In terms of the most frequently used self-service banking technologies, 59% have used smartphones (both apps and SMS), 21% have used regular phones (SMS alone), 4% have used POS, and approximately 15% have used ATM. Besides regular subscription for airtime, data, and TV, fund transfer (especially to relative and friends) is the most used e-banking services among respondents.

Despite a large fraction of respondents being business owners, e-banking payments for services rendered (purchases) are not utilised. I argue here, and as observed in the subsequent section, that the reasons for the low adoption of e-payment among these respondents are two-fold: (1) Digital infrastructural failure - This is when the e-banking payment platform fails during a transaction and creates uncertainty about the outcome of the transaction, and (2) e-fraud, and distrust created by e-fraudsters among victims.

Table 7.2a. Distribution of respondents according to e-banking adoption

Panel A: Economic, social, and demographic features											
Demography		Frequency	Percent	Marital Status	Frequency	Percent					
Rural		330	30	Not married	421	37					
Urban		798	70	Married	707	63					
Total		1128	100	Total	1128	100					
Age		Frequency	Percent	Annual Income (USD)	Frequency	Percent					
<20		34	3	<300	388	40					
20-30		329	29	300-600	325	33					
31-40		488	43	601-900	154	16					
>40		277	25	>900	106	11					
Total		1128	100	Total	973	100					
Education		Frequency	Percent	Employment Status	Frequency	Percent					
Primary or less		75	8	Not employed	122	10					
Secondary		319	28	Self-employed	542	48					
Post-secondary [†]		323	29	Informally employed	133	12					
Tertiary		411	37	Formally employed	354	31					
Total		1128	100	Total	1128	100					
Gender		Frequency	Percent	Formal association	Frequency	Percent					
Male		758	67	Yes	749	66					
Female		370	33	No	379	34					
Total		1128	100	Total	1128	100					
Panel B: Financial access											
		Rural		Urban				Rural		Urban	
		Freq	%	Freq	%			Freq	%	Freq	%
Bank branch within	<1KM	150	45	437	55	ATM/MM outlet within	<1KM	204	62	499	63
	1-2KM	54	16	225	29		1-2KM	23	7	211	27
	>2KM	126	38	136	17		>2KM	103	31	88	11
	Total	330	100	798	100		Total	330	100	798	100
Bank branches within 1KM	0	133	40	172	22	ATM/MM outlets within 1KM	0	82	25	72	9
	1	93	28	143	18		1	16	5	46	6
	2	25	8	110	14		2	34	10	105	13
	3 or more	79	24	373	47		3 or more	198	60	575	73
	Total	330	100	798	100		Total	330	100	798	100

[†] Includes diploma or certificate completion.

Table 7.2b. Distribution of respondents according to e-banking adoption

Panel C: e-banking adoption and usage					
Own a bank account	Freq.	Percent	Use e-banking (MR)	Freq.	Percent
No	8	1	No	52	5
Yes	1120	99	Yes	1076	95
Total	1128	100	Total	1128	100
Digital Devices owned (MR)	Freq.	Percent	e-banking platforms (MR)	Freq.	Percent
Not Smartphone	662	33	Internet/mobile Apps	547	28
Smart phone/tablet	884	44	SMS banking	954	48
PC/laptop	297	15	Mobile Money Banking	168	8
POS	134	7	POS	253	13
Total	1996	100	Total	1983	100
Most used e-banking (SSBTs)	Freq	Percent	e-banking usage (MR)	Freq.	Percent
Smart mobile phone/tablet	666	59	Subscription (airtime, data, TV, etc.)	937	29
mobile phone (not smart)	233	21	Fund transfer	860	27
PC/laptop	6	1	Purchase ^φ	447	14
POS	48	4	Withdrawal	561	17
ATM	169	15	Bills payment ^ψ	340	11
Total	1128	100	Total	3207	100
e-banking most used services	Freq.	Percent	Freq. of most used services	Freq.	Percent
Bills payment	30	3	everyday	272	24
Fund transfer (to friends/relative)	544	48	4/week	190	17
Purchases	154	14	2/week	214	19
Withdrawal	320	28	Weekly	235	21
Others	80	7	2/month	98	9
Total	1128	100	Monthly	119	11
			Total	1128	100

MR - multiple responses.

^φ Payment for goods and services

^ψ School fees, rent, NEPA, gas, water, etc.

7.5.2. Challenges of electronic banking in Nigeria

To understand the challenges of e-banking among users, I evaluate their feeling and experience with e-banking transactions, and whether or not they have been victims of e-fraud. Table 7.3 shows that approximately 75% of respondents feel uneasy (scared) either occasionally, sometimes, or usually when performing some forms of electronic banking operations. In addition to other factors identified, approximately 40% of respondents have either personally lost money or know someone who has lost money through electronic banking. The result shows that less than half of all monies lost via electronic banking are recovered (panel B of Table 7.3). As noted in the literature review, e-fraud is widespread

in Nigeria's financial systems. The sources of these e-frauds as identified by respondents include users' card or personal bank details stolen either directly from users or through bank and service providers. This constitutes 28% of the e-fraud incidence in our sample. This form of e-fraud is widespread and has caused economic pains among users. E-banking users are protected by consumer protection right enshrined in the payment system guidelines of the CBN, especially in the case of data breaches from bank or service provider. However, this guideline is not strictly enforced and there seems to be complicity from infrastructure, technology, and service providers. There also seem to be weak implementation or enforcement of the payment guidelines by regulatory authorities tasked with enforcing e-fraud conflict-related complaints. This can be seen from the repeated occurrence of e-fraud, implying that respondents possibly fell victims to e-fraud at least twice as indicated by 46% of victims. Furthermore, 42% of the victims have foregone the right to have their money refunded after many attempts, implying that victims' attempts to recover stolen money have not been successful.

On consumer protection awareness, approximately 42% of victims either reported the incidence of e-fraud to the government, a private agency, or took legal action. First, this category of victims may have been knowledgeable about user protection rights. Second, this category of victims may be economically equipped to push their case through many recovery channels. In contrast, more than half of victims either did nothing or had no idea where to report the e-fraud incidence to. Given that many respondents in our sample are educated, this might be a problem of awareness. Victims with less economic power tend to suffer e-fraud incidences given that regulatory authorities are not responsive about e-fraud related matters. Furthermore, since there are regulatory failures, victims bear the cost of recovering money stolen through e-fraud. Therefore, the amount of money stolen will determine whether victims should use other personal resources to recover it. Moreover, given that most respondents are low-income earners and self-employed (business owners), using additional resources to recover stolen money (without guarantee) is a futile exercise. In general, while a larger fraction (63%) of the respondents may take actions in the event of e-fraud, at least a third of all respondents (victims and non-victims) may not take any action in the event of e-fraud.

Table 7.3. e-fraud and consumer protection awareness

Scared during e-banking transaction	Freq	Percent	How it happened	Freq	Percent	
Never	264	23	Card/personal details stolen from users	97	20	
occasionally (10-30%)	437	39	Card/personal details stolen from bank or service providers	41	8	
sometimes (50%)	304	27	Network errors yet debited*	312	63	
Usually (70-90%)	90	8	Others	46	9	
Every time (100%)	33	2.9	Total	496	100	
Total	1128	100				
Lost money through e-banking	Freq	Percent	Need internet for e-banking	Freq	Percent	
No	700	62	No	602	53	
Yes	428	38	Yes	526	47	
Total	1128	100	Total	1128	100	
Frequency of occurrence	Freq	Percent	How was the case resolved	Freq	Percent	
once	229	54	I have foregone after many attempts	73	42	
twice	95	22	It was ignored	42	24	
More than twice	102	24	Pending/on-going	60	34	
Total	426	100	Total	175	100	
Lost money recovered	Freq	Percent	Money recovered through 3rd party	Freq	Percent	
No	171	40	No	169	66	
Yes	255	60	Yes	86	34	
Total	426	100	Total	255	100	
When bank failed to refund you...	Freq	Percent	If bank fail to refund you...	Freq	Percent	
Report to Govt agency	58	28	Report to Govt agency	434	39	
Report to Private/NGO	11	5	Report to Private/NGO	61	5	
Took legal action	18	9	Take legal action	210	19	
No idea who to report to	53	26	No idea who to report to	221	20	
Did nothing because I was helpless	66	32	Do nothing because I maybe helpless	193	17	
Total	206	100	Total	1119	100	
Panel B	N	Sum	Mean	Std	Min	Max
Amount lost (\$)	425	43,743.92	102.93	195.18	2.78	2,500.00
Amount recovered (\$)	255	20,992.29	82.32	159.65	2.78	1,388.89

7.5.3. Determinants of electronic bank adoption in Nigeria

This section tests the general hypothesis about the relationship between users' physical features (IC) and devices, platform, and services, as well as the specific relationships between the sub-variables.

Figure 7.4 shows the estimated standardised path coefficients between the latent variables³⁷. Our interest, however, is the correlation between these latent variables (in

³⁷ Unstandardized path coefficients are significant and are reported in Appendix 7C1. Standardizing converts the covariances to correlations which have straightforward interpretations. Some goodness of fit statistics on Appendix 7C2 suggest the model fit is

oval shapes). The result shows a significant positive relationship between individual characteristics (IC) estimated from age, employment, education, annual income, nearness to bank, and type of *devices owed*, type of *platform adopted*, and type of *e-banking services adopted*.

There is a high and positive correlation between IC and e-banking platform (63%), and IC and e-banking services adopted (64%), implying that users' economic, social, and demographic characteristics determine the e-banking platform and the e-banking service adopted. Simply put, the type of e-banking platforms or services adopted can be characterised by the users' (economic and social) characteristics. Undoubtedly, and as expected, the type of device used is strongly correlated with e-banking platforms (73%). The latter is also strongly correlated with services (78%).

The correlation between devices and user characteristics (30%), though significant, is weak. This is due to the closing digital divide, and the flexibility and versatility of the e-banking system in Nigeria. First, as noted earlier, the growing internet and mobile penetration suggests that users can now own a form of digital device irrespective of economic, social, and demographic characteristic. Second, the changing service innovations and financial technologies have made it possible to conduct many e-banking services regardless of the devices. In conclusion, the estimated correlations between latent variables (IC, platform, and services) show that we cannot reject our broad hypotheses (H_1 , H_2 and H_3)

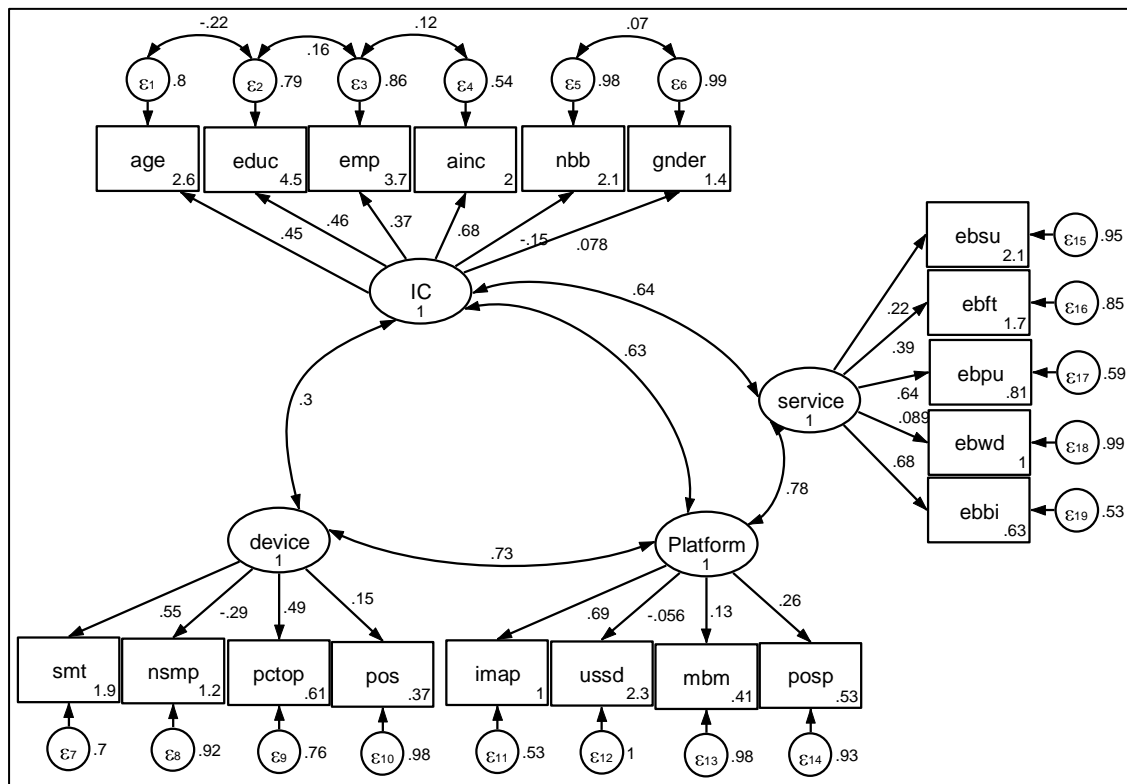


Figure 7.4. The estimated relationship between latent variables

Next, I investigate the direct relationship between the sub-variables (observed endogenous variables) where we wish to establish the specific determinants of e-banking adoption (platforms and services) from a pool of users' socioeconomic characteristics. As described in the empirical equations (7.1-7.6), I use the Bernoulli logistics function and multinomial logistics since our response variables are binary and categorical variables. Figure 7.5 shows the estimated transformed GSEM path coefficients in two panels (platform and service adopted, respectively)³⁸. Table 7.4a shows the summary of the coefficient of logistics GSEM results in Figure 7.5.

On e-banking platform adoption, the result shows that age, education, types of employment, annual income, and financial access are significant determinants of e-

³⁸ The result in Figure 8.5 is equivalent to running 8 logistics regressions as seen in Table 4.

banking adoption. This is consistent across all e-banking platforms except SMS banking, where education has no impact.

The odds of adopting internet or mobile banking (using bank enabled apps) decreases with older respondents. This implies that older users are less likely to adopt internet or mobile banking that uses a bank or third party enabled applications. This might be due to difficulty in operating these internet banking applications where users are required to provide several gate passes (passwords). Interestingly, the odds of adopting this e-banking platform increases among users with higher education attainment and higher annual income, as well as formally employed users as opposed to the informally employed or self-employed. More educated people are more likely to explore internet/mobile apps platforms that provide multi-service benefits and flexibility. Furthermore, high-income earners are also more likely to adopt such platforms since they offer higher single or daily transaction limit.

The odds of SMS (ussd) banking and mobile money banking adoption increase with older users. This is because the former offers an easy interface and requires less complicated security protocol when performing bank operations, while the latter is merely a third-party bank agent that delivers bank services. Furthermore, formally employed users are less likely to use these platforms than informally employed users. Again, this may be due to the limited amount that can be transacted on these platforms. Similarly, the odds of adopting SMS and mobile money banking decreases with higher income earners.

The odds of adopting a POS platform, which offers more robust transactions, increase with higher income earners, especially among business owners. Relatedly, the odds of adopting a POS platform is higher for informally employed (including self-employed) relative to formally employed and non-employed users. This result suggests that the adoption of POS among small businesses is more. This result is in line with an earlier study by Ene et al. (2019) that found POS to have significantly improved financial inclusion in Nigeria. Furthermore, males are more likely to adopt internet, mobile banking, and SMS banking, but are less likely to adopt mobile money and POS banking compared to females. Lastly, and as expected, the likelihood of adopting these e-banking platforms is higher among users with less access to bank branches.

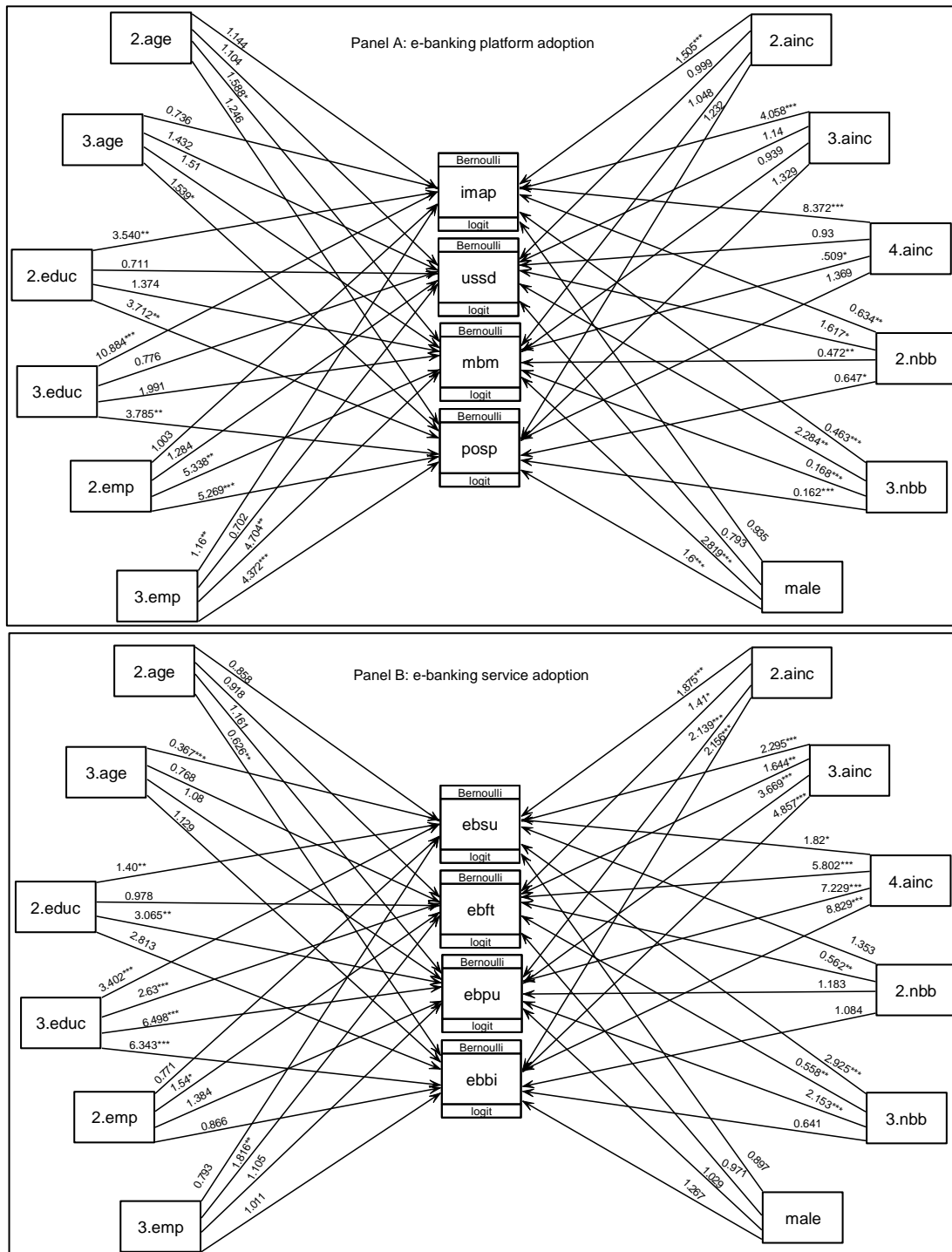


Figure 7.5. GSEM estimates of socioeconomic characteristics and e-banking adoption

On e-banking services, the result shows that the odds ratios decrease with older users of e-banking services such as subscriptions, fund transfer, and purchases, but increases with older users of services such as bills payment. The likelihood to adopt the former increases with higher education attainment. The odds for the adoption of subscriptions, fund transfer, and bills payment are also higher for formally employed users, high-income earners, and users with less access to physical banks. Furthermore, the odds for e-banking purchase (payment for services rendered) and withdrawal decreases for informally employed users relative to formally and non-employed users. However, the likelihood for the adoption of these services increases among users with high income and users with less access to physical bank branches. Lastly, compared to females, males are more likely to adopt e-banking subscription and e-banking fund transfer, and less likely to adopt e-banking payment and e-banking bills payment. These results show that the dynamics of electronic banking adoptions in Nigeria are determined by users' social, economic, and demographic features. Most importantly, age, gender, educational attainment, employment types, income, and financial access are determinants of electronic banking adoption.

Figure 7.4b shows the result of the multinomial logistics model, which describe the relationship between users' characteristics and the most frequently used platform among adopters in our sample. The results show that the relative log-odds for adopting smartphone or tablet (smt), POS, and non-smartphone (nsmp) as the frequently used platforms over ATM decrease with older users. However, the relative log-odds of adopting smartphone/tablet and POS increase with higher education attainment. Similarly, the relative log-odds of smartphone/tablet and non-smartphone banking are higher for formally employed users when compared to informally employed or non-employed users. Concerning annual income, the relative log-odds of adopting all the three platforms over ATM increase with high-income earners.

On the contrary, the relative log-odds of adopting e-banking payment system (ebpu) and fund transfer (ebft) as the most frequent e-banking services relative to withdrawal (ebwd) decreases with older users. The relative log-odds of e-banking service such as bill

payment increase with the older respondents. In general, these results seem to validate and support our earlier findings using the binary logistic model.

Table 7.4a. Outputs from the GSEM Estimation (Bernoulli logistics model)

Dependent variable: e-banking platform/services adoption-yes

	e-banking platform				e-banking services			
	imap	ussd	mbm	posp	ebsu	ebft	ebpu	ebbi
bn.age								
2.age	1.144 (.194)	1.104 (.228)	1.588* (.378)	1.246 (.252)	.858 (.183)	.918 (.168)	1.161 (.198)	.626** (.122)
3.age	.736 (.154)	1.432 (.368)	1.51 (.423)	1.539* (.355)	.367*** (.088)	.768 (.173)	1.08 (.22)	1.129 (.245)
1.male	.935 (.14)	.793 (.148)	2.8*** (.676)	1.6*** (.286)	.897 (.165)	.971 (.16)	1.029 (.154)	1.267 (.209)
1bn.educ								
2.educ	3.54** (.181)	.711 (.364)	1.374 (.61)	3.712** (2.07)	1.4 (.481)	.978 (.307)	3.065** (1.548)	2.813 (1.791)
3.educ	10.8*** (5.457)	.776 (.391)	1.991 (.852)	3.785** (2.083)	3.40*** (1.183)	2.63*** (.832)	6.49*** (3.218)	6.34*** (3.949)
1bn.emp								
2.emp	1.003 (.267)	1.284 (.416)	5.33** (3.959)	5.27*** (2.847)	.771 (.242)	1.54* (.396)	1.384 (.407)	.866 (.294)
3.emp	1.164 (.337)	.702 (.245)	4.704** (3.56)	4.37*** (2.434)	.793 (.279)	1.816** (.536)	1.105 (.349)	1.011 (.362)
bn.ainc								
2.ainc	1.505** (.264)	1 (.22)	1.048 (.234)	1.232 (.25)	1.875*** (.398)	1.41* (.264)	2.139*** (.386)	2.156*** (.463)
3.ainc	4.058*** (.939)	1.14 (.327)	.939 (.271)	1.329 (.336)	2.295*** (.657)	1.644** (.412)	3.669*** (.82)	4.857*** (1.202)
4.ainc	8.372*** (2.549)	.93 (.302)	.509* (.189)	1.369 (.392)	1.82* (.576)	5.802*** (2.488)	7.229*** (1.98)	8.829*** (2.503)
bn.nbb								
2.nbb	.634** (.138)	1.617* (.439)	.472** (.157)	.647* (.162)	1.353 (.352)	.562** (.13)	1.183 (.252)	1.084 (.249)
3.nbb	.463*** (.135)	2.284** (.914)	.168*** (.102)	.162*** (.083)	2.925*** (1.199)	.558** (.161)	2.153*** (.601)	.641 (.213)
_cons	.095*** (.053)	5.496*** (3.185)	.007*** (.006)	.013*** (.01)	1.75 (.784)	1.159 (.455)	.052*** (.029)	.045*** (.031)
chi2	277.483	42.112	54.596	115.119	95.878	121.911	207.898	227.209
p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Obsev.	1071	1071	1071	1071	1071	1071	1071	1071
r2_p	0.173	0.043	0.085	0.104	0.087	0.10	0.136	0.17

Table 7.4b. Outputs from GSEM estimation (Multinomial logistics model)
Dependent variable: most frequently used platform/service

	Most frequently used platform				Frequently used services			
	smt	posp	nsmp	atm	ebpu	ebft	ebbi	ebwd
1bn.age								
2.age	0.713*** (0.243)	0.474 (0.435)	0.959*** (0.275)		2.185*** (0.513)	1.829*** (0.482)	2.201*** (0.496)	
3.age	0.263 (0.281)	0.259 (0.505)	0.344 (0.329)		1.136** (0.567)	1.052** (0.525)	2.868*** (0.541)	
1bn.educ								
2.educ	0.500 (0.449)	1.884* (1.115)	0.600 (0.460)		1.165 (1.217)	0.720 (1.125)	1.099 (1.142)	
3.educ	1.207*** (0.443)	2.420** (1.106)	0.374 (0.465)		1.559 (1.181)	0.702 (1.092)	0.683 (1.111)	
1bn.emp								
2.emp	1.422*** (0.321)	1.759*** (0.598)	2.053*** (0.378)		0.947 (1.205)	0.565 (1.119)	0.386 (1.117)	
3.emp	1.532*** (0.361)	0.514 (0.751)	2.227*** (0.431)		0.480 (1.274)	1.178 (1.181)	0.627 (1.184)	
1bn.ainc				Constraint				Constraint
2.ainc	2.341*** (0.239)	1.853*** (0.468)	1.375*** (0.271)		1.308** (0.640)	0.582 (0.603)	0.316 (0.611)	
3.ainc	5.053*** (0.354)	7.703*** (0.555)	1.662*** (0.421)		0.418 (0.633)	0.138 (0.588)	0.046 (0.613)	
4.ainc	5.877*** (0.403)	4.010*** (0.727)	1.757*** (0.503)		6.154*** (1.176)	1.916* (1.150)	0.226 (1.191)	
1bn.nbb								
2.nbb	2.630*** (0.317)	3.602*** (0.487)	2.292*** (0.371)		1.818*** (0.682)	2.313*** (0.643)	3.776*** (0.658)	
3.nbb	14.358*** (0.683)	6.013*** (0.988)	12.508*** (0.710)		1.060 (0.648)	0.348 (0.619)	0.862 (0.629)	
_cons	1.412*** (0.507)	0.073 (1.204)	0.789 (0.550)		2.765* (1.620)	49.527*** (1.497)	54.596*** (1.509)	
Chi2		1090				1090		
P		309.165				240.636		
		0.000				0.000		

Robust standard errors are in parenthesis.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

7.6. Summary of results and conclusion

This study focuses on the adoption of e-banking among users from all walks of life, with emphasis on business owners, the challenges of e-banking, and the determinants of e-banking adoption. I define e-banking using a broader view as opposed to other researchers. The novelty of this study is the application of GSEM to determine the relationship between users' physical characteristics and the odds of adopting specific e-banking

platforms and services. This framework has not been explored in electronic banking studies yet.

The findings show evidence of financial deepening in the study areas both in terms of access to self-service banking technologies, such as ATMs and mobile money operators, and e-banking adoptions among respondents. The findings also indicate that there is low adoption of e-banking payment services among respondents due to widespread electronic fraud. The consequence of widespread electronic fraud is distrust among electronic banking users. Another factor mitigating the adoption of e-banking payment are poor payment infrastructures or gateways where service interruption or network failures during financial transaction mean that users could lose money.

These results have huge implications, especially in the light of the two current monetary policies aggressively pursued by the Nigerian government: the cashless policy and the financial inclusion strategy. For example, the idea behind the cashless policy was to promote the adoption of electronic payments which has overarching economic benefits of reducing cash outside the banks (eliminate shadow economy), combatting corruption, and reducing the cost of cash handling. Furthermore, the financial inclusion strategy was designed to improve local financial integration by reducing the unbanked populations. These policies liberalised the financial system, increased mobile money operators, and more recently, provided licenses to PSBs. The PSBs enable mobile operators to offer digital financial services, potentially reaching all GSM users in Nigeria. The rationale is simple: since mobile penetration is projected to rise continuously into the future, access to mobile phones could also mean access to financial services.

The success of these two policies depends on a large-scale adoption/diffusion of electronic banking, more specifically, electronic banking payments. However, as demonstrated by the findings, the low acceptance of electronic banking payments is arguably a setback for the cashless policy and the financial inclusion strategy. The economic implications of these two policies cannot be overemphasised. Because digital banking is the only means to drive these policies, there should be policy consolidations that encourage the adoption of e-banking payment among small businesses and individuals. Such strategies must include digital infrastructural upgrade and prompt

response to e-fraud conflict-related issues. In addition, awareness about how and where to report cases of e-fraud, besides the host financial institutions, is critical since host banks are complicit as shown by this study.

This could be achieved in three ways: First, financial institutions could be mandated to report all e-fraud incidences to regulators and provide all details including possible conflict of interests or negligence. Second, service providers must also provide users with regular up-to-date contacts, including regulators' contacts where e-fraud incidents can be reported. Third, regulators could create and disseminate knowledge about recovering monies lost through e-fraud on radios, TV, or through SMS to registered e-banking users. These steps are critical to restoring confidence among e-banking users.

The findings on the determinants of electronic banking adoption indicate that there is a correlation between users' socioeconomic and physical characteristics and the e-banking platform or services adopted. This result is both informative and instructive. It reveals that the odds of adopting different e-banking platforms and services differ across users' age group, education attainment, types of employment, annual income, and users' access to other financial facilities. These findings have implications for innovators and service providers. Innovators of financial technologies must simplify the functionalities of these technologies to suit users' needs and sophistication. Meanwhile, service providers must also simplify financial services and tailor them to the physical and economic needs of users as documented in this study.

Appendix 7A

Survey

Questionnaire Title: Determinants of electronic banking and other SSBTs usages in Nigeria

Description: This survey is designed to elicit information on all kinds of electronic banking and other Self-Service Banking Technologies (SSBTs). SSBTs include; internet/mobile banking, SMS banking, POS, ATMs and other bank technologies that allow financial related transactions electronically.

Purpose: The purpose of this survey is to evaluate the dynamics of information technology learning and the economic impact of electronic banking on the Nigerian economy and people.



Appeal: If you agree to participate in this survey, kindly complete all sections that apply to you as accurate as possible. The survey takes about 15 minutes to complete. Thank you for your cooperation.

Section one: Demographic										
1. GPS coordinates (Will be automatically captured).										
2. State:										
3. Demographic location				Rural			urban			
4. Age		<20		20-30		31-40		>41-50		
5. Gender				Female			Male			
6. Marital Status				Married			Not Married			
7. Education attainment		Primary or less		Secondary		Post-secondary: Diploma/cert		Tertiary: BSc/BA/HND Masters/Phd		
8. Can you read and write in English language?						Yes		No		
9. Can you read in your mother-tongue?						Yes		No		
10. Can you write in your mother-tongue?						Yes		No		
11. Employment Status		None		Self Employed		Employed informally		Employed formally		
12. Annual Income ('000)		<300		300-600		601-900		>901-1.2M		
13. Monthly income ('000)		<30		30-60		61-90		>91-120		
14. Disposable Income (income available for spending after taxes and expenses have been deducted)								₦:		
15. Do you belong to any formal or informal association (e.g. cooperative, local community, sales or business group, etc.)?								Yes		No
16. If Yes, how many times do you meet in a year?						2		4		6
17. Do you belong to any SNS or social media group/platform								Yes		No
Section two: Electronic banking (internet, mobile, SMS, ussd code, POS & ATMs) usage										
18. How many bank branches can be found within 1KM from your house/office/shop/store?										
19. How far (in KM) is the nearest bank branch from your house/office/shop/store?						<1KM		1-2KM		>2KM
20. How many ATMs (or MM outlets) can be found within 1KM distance from your house/office/shop/store?										
21. How far (in KM) is the nearest ATM (or MM outlets) from your house/office/shop/store?						<1KM		1-2KM		>2KM
22. Do you have the following device(s)? multiple answers allowed (MAA)				PC/Laptop			Smart Mobile/tablet			
				Mobile Phone (Not smart)			POS		Others	
23. Years of experience in using any of the devices above						_____ years;				
24. Do you have a bank account?				Yes			No			
25. Do you have an e-banking system (internet/mobile banking, SMS/ussd banking etc) enabled on your device?						Yes		No		
26. Which of these e-banking systems/apps do you use? multiple answers allowed (MAA)				Internet/mobile banking apps			SMS banking (using USSD code)			
				POS payment apps			Others			
27. Which one of these devices/platforms is the most frequently used for your e-banking services?				PC/laptop			Smart mobile phone/tablet		POS	
				mobile phone (not smart)			ATM		Others	
28. Reason(s) for your answer in Qn. 27? (MAA)		Convenient		Lower cost		Safe time		Ease of use		Available 24/7
										Others
29. What language(s) is your e-banking system in? (MAA)				English		Hausa		Igbo		Yoruba
										Others
30. Is your e-banking system ALSO in your local language? (Local language=first language or mother tongue)								Yes		No
31. If No, do you wish that your e-banking system is ALSO in your local language?				Yes		No, I can't read in my local language			It doesn't matter to me	
32. Which of the following best describe your usage of e-banking systems? (MAA)				Subscriptions (airtime & data, TV, etc)			Bills payment (Sch. fees, rent, NEPA, Gas, etc.)			
				Purchases (payment for goods & services)			Fund transfer (to friends/relative)		Withdrawal	
									Others	
33. Besides regular subscriptions for airtime & data, TV, etc., which ONE of these e-banking services is your most frequently used service?				Purchases (payment for goods & services)			Fund transfer (to friends/relative)		withdrawal	
									Others	

34. On average, how often do you use your most frequently used e-banking service or platform (in Qn. 33)?				everyday	4/week	2/week	
				Weekly	2/month	Monthly	
35. How long (in mins) does it take to complete your most frequently used e-banking service (in Qn. 33)?					_____ mins		
36. Estimate the total cost in Naira (e.g. sms cost, bank charge, VAT, etc.) for your most frequently used e-banking service/transaction (in Qn. 33).						₦	
37. How satisfied are you with your most frequently used e-banking service or platform (in Qn. 33)?				Very satisfactory	Satisfactory	Neutral	
				Unsatisfactory	Very unsatisfactory		
38. How secure is your most frequently used e-banking system or platform (in Qn. 33)?				Very secure	Secure	Undecided	
				Insecure	Very insecure		
39. How efficient is your e-banking system/platform				Very efficient	Efficient	Neutral	
				Inefficient	Very inefficient		
40. How reliable is your e-banking system/platform?				Very reliable	Reliable	Neutral	
				Unreliable	Very unreliable		
41. Do you need internet access in your device to use your e-banking system/apps?					Yes	No	
42. In general, do you use or have internet access on your device?					Yes	No	
43. Estimate the monthly cost of your internet subscription						₦	
44. How reliable is your internet service?	Very reliable	reliable	somewhat reliable	neutral	somewhat unreliable	unreliable	very unreliable
Section three: Theft and Consumer Protection Awareness							
45. I get scared or feel uneasy when performing some e-banking transactions.			Usually (70-90%)	sometimes (50%)	occasionally (10-30%)	Never	
46. Have you or someone you know lost money through e-banking?					Yes	No	
47. If yes, how did it happen? (multiple answers allowed)	The card/security details were stolen from me/him/her directly	The card/security details were stolen through my/his/her bank/service provider			Network error/failure during transaction yet the account was debited	Others	
48. How many times has this happened to you or someone you know?				Once	Twice	More than twice	
49. Please give the approximate amount that you or someone you know lost through e-banking.						₦:	
50. Was the lost money recovered (in whole or in part)?					Yes	No	
51. If yes, please give the approximate amount recovered					₦:		
52. Was a third party helpful in recovering the money?					Yes	No	
53. If No in Qn. 50 above, how was the issue resolved?		Ignored	Pending/still on-going	I decided to forget about it after many attempts			
54. When the bank(s) failed to refund the stolen money, what did you or the affected person do? (MAA)		Reported to Govt. agency		Reported to private agency/NGO			
		Took legal action Went to the Court		Did nothing because I was helpless		I had no idea who/which agency to report to	
55. If the bank(s) fail to refund money stolen from your account, what will you do?		Report to Govt. agency		Report to private agency/NGO			
		Take legal action (seek redress in the Court)		Do nothing since I maybe helpless		I have no idea who/which agency to report to	

Appendix 7B

DataScope mobile apps e-form

 DataScope EMAIL OR USERNAME Please enter your Email or Username.... PASSWORD Please enter your Password.... LOGIN NEW ACCOUNT	 Available Forms Here you can see all your available forms, you can create more in the web platform. SURVEY ON ELECTRONIC BANKI... > DOOR TO DOOR FPSD IN ONDO... > + NEW FORM
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Appendix 7C1 Outputs from SEM

*Endogenous variables- Measurement: age educ emp ainc nbb natmm smt nsmp pctop pos imap ussd
mbm posp ebsu ebft ebpu ebwd ebbs*

Exogenous Variables-Latent: IC devices Platform services

Structural equation model (Number of obs = 1,128)

Estimation method = mlmv (Log likelihood = -14307.245)

	OIM					
	Coef.	Std.Err.	z	P>z	Interval]	
	[95% Conf.					
Measurement						
age <-						
IC		1		(constrained)		
_cons	1.918	0.023	83.810	0.000	1.873	1.963
educ <-						
IC	0.793	0.120	6.610	0.000	0.558	1.028
_cons	2.610	0.018	147.280	0.000	2.575	2.644
emp <-						
IC	0.670	0.087	7.660	0.000	0.498	0.841
_cons	2.240	0.018	122.090	0.000	2.204	2.276
ainc <-						
IC	1.969	0.176	11.210	0.000	1.625	2.314
_cons	1.957	0.030	66.190	0.000	1.899	2.015
nbb <-						
IC	-0.365	0.103	-3.560	0.000	-0.566	-0.164
_cons	1.706	0.025	68.810	0.000	1.657	1.754
gnder <-						
IC	0.110	0.051	2.170	0.030	0.011	0.209
_cons	0.673	0.014	46.980	0.000	0.645	0.701
smt <-						
devices		1		(constrained)		
_cons	0.789	0.012	63.280	0.000	0.765	0.813
nsmp <-						
devices	-0.635	0.115	-5.510	0.000	-0.860	-0.409
_cons	0.589	0.015	39.190	0.000	0.560	0.619
pctop <-						
devices	0.985	0.228	4.320	0.000	0.538	1.432
_cons	0.272	0.014	19.990	0.000	0.245	0.298
pos <-						
devices	0.223	0.121	1.840	0.065	-0.014	0.460
_cons	0.122	0.010	12.220	0.000	0.103	0.142
imap <-						
Platform		1		(constrained)		
_cons	0.481	0.014	33.350	0.000	0.453	0.509
ussd <-						
Platform	-0.064	0.036	-1.770	0.076	-0.135	0.007
_cons	0.838	0.011	74.330	0.000	0.815	0.860
mbm <-						
Platform	0.142	0.038	3.750	0.000	0.068	0.216
_cons	0.145	0.011	13.490	0.000	0.124	0.166
posp <-						
Platform	0.329	0.044	7.480	0.000	0.243	0.415
_cons	0.214	0.012	17.220	0.000	0.189	0.238
ebsu <-						
services		1		(constrained)		

_cons	0.812	0.012	68.090	0.000	0.789	0.836
ebft <-						
services	1.996	0.366	5.450	0.000	1.278	2.713
_cons	0.746	0.013	56.090	0.000	0.720	0.772
ebpu <-						
services	3.699	0.641	5.770	0.000	2.443	4.954
_cons	0.395	0.015	26.440	0.000	0.366	0.424
ebwd <-						
services	0.531	0.246	2.160	0.031	0.049	1.013
_cons	0.506	0.015	33.130	0.000	0.476	0.536
ebbi <-						
services	3.673	0.635	5.780	0.000	2.429	4.918
_cons	0.287	0.014	20.750	0.000	0.260	0.314
var(e.age)	0.449	0.025			0.403	0.501
var(e.educ)	0.266	0.016			0.236	0.300
var(e.emp)	0.310	0.017			0.279	0.346
var(e.ainc)	0.503	0.050			0.415	0.610
var(e.nbb)	0.643	0.028			0.590	0.701
var(e.gnder)	0.219	0.009			0.201	0.238
var(e.smt)	0.117	0.016			0.090	0.151
var(e.nsmpt)	0.222	0.014			0.195	0.252
var(e.pctop)	0.149	0.011			0.130	0.172
var(e.pos)	0.105	0.005			0.096	0.115
var(e.imap)	0.118	0.016			0.091	0.154
var(e.ussd)	0.136	0.006			0.125	0.148
var(e.mbm)	0.121	0.005			0.111	0.132
var(e.posp)	0.154	0.007			0.141	0.168
var(e.ebsu)	0.145	0.006			0.133	0.159
var(e.ebft)	0.161	0.008			0.147	0.177
var(e.ebpu)	0.142	0.009			0.126	0.160
var(e.ebwd)	0.248	0.011			0.228	0.270
var(e.ebbi)	0.109	0.007			0.095	0.124
var(IC)	0.112	0.021			0.077	0.162
var(devices)	0.050	0.016			0.027	0.092
var(Platform)	0.105	0.018			0.075	0.146
var(services)	0.007	0.002			0.004	0.014
cov(e.age,e.educ)	-0.078	0.012	-6.240	0.000	-0.102	-0.053
cov(e.educ,e.emp)	0.045	0.012	3.690	0.000	0.021	0.068
cov(e.emp,e.ainc)	0.046	0.023	2.030	0.042	0.002	0.090
cov(e.nbb,e.gnder)	0.026	0.012	2.280	0.023	0.004	0.049
cov(IC,devices)	0.022	0.005	4.450	0.000	0.012	0.032
cov(IC,Platform)	0.068	0.008	8.750	0.000	0.053	0.083
cov(IC,services)	0.018	0.004	5.060	0.000	0.011	0.025
cov(devices,Platform)	0.053	0.005	9.820	0.000	0.042	0.064
cov(Platform,services)	0.021	0.004	5.390	0.000	0.014	0.029

LR test of model vs. saturated: $\chi^2(143) = 2356.99$, Prob > $\chi^2 = 0.0000$

Appendix 7C2

Goodness of fit test

Fit statistic	Value	Description
Population error		
RMSEA	0.117	Root mean squared error of approximation
90% CI, lower bound	0.113	
upper bound	0.121	
pclose	0.000	Probability RMSEA <= 0.05
Information criteria		
AIC	28746.490	Akaike's information criterion
BIC	29078.351	Bayesian information criterion
Baseline comparison		
CFI	0.574	Comparative fit index
TLI	0.491	Tucker-Lewis index
Size of residuals		
CD	0.952	Coefficient of determination

Note: SRMR is not reported because of missing values.

Chapter 8

Conclusions and Implications

8.1. Introduction

This chapter presents a summary of the findings, implications, and policy recommendations. The chapter concludes with the limitations of the study and offers some future directions.

8.2. Summary: Objectives and findings

In this research, I addressed the question of whether bank experience could affect financial intermediary efficiency. More specifically, I looked at whether bank experience reduces the cost of credit creation, debt management, and value creation (shareholder value and the gross value added to the economy). Addressing these questions requires studying the learning curve of banks for which there was no suitable empirical method. Therefore, this research derived a dynamic cost function that incorporated learning. Then, I applied this function to Nigerian commercial banks to measure learning through credit creation (investment and risk-taking) and value creation (efficiency of lending to the real sector and service provision).

I also addressed other questions on the adoption and diffusion of electronic banking and payment technologies in Nigerian commercial banks. For example, with the rapid introduction of financial technologies and payments system in Nigeria, some policy questions emerged: To what extent are these technologies diffused or what is the current level of diffusion of some financial technologies in Nigeria? What are the determinants (social and economic) and challenges facing diffusion/adoption of financial technologies and electronic banking in Nigeria?

This research systematically addressed the research questions by employing panel data fixed effect regression, technology forecasting models, and generalised structural equation modelling. The main findings are summarised below.

On learning by banking, the findings indicated that the efficiency gains from experience lower the unit cost of producing both additional credit and gross value added in Nigeria's

commercial banks. This finding implies that asset transformation, which is the thrust of bank intermediary activities, requires experience. This experience comes from sustained efforts in the value creation processes, continuous monitoring and screening of potential borrowers, and from the information-intensive processes involved in investment and risk management that return positive yield. One practical implication of this finding is that bank experience in credit and value creation is an important determinant of bank productivity. However, Nigerian commercial banks failed to create positive economic profits (economic value added), which suggests substantial shareholder value destruction.

The findings on the diffusion of financial payment technologies indicated that digital technological learning has significantly improved financial access, financial inclusion, and reduced the number of unbanked populations. More specifically, the findings indicate that the diffusion of digital payment systems such as ATM, POS, and Web will peak between the years 2027 and 2030, whereas the diffusion of mobile payments is forecasted to last several years into the future. This finding implies that the mobile payment system is an important platform to drive financial inclusion and the cashless policy, especially among the unbanked population.

The findings on the adoption and determinants of electronic banking also indicate substantial financial deepening in terms of the widespread adoption of electronic banking and other self-service banking technologies. However, the findings also showed that poor digital security infrastructure has led to widespread electronic fraud. In turn, this has led to low acceptance of e-payment among small business owners. This is a huge setback for the cashless economy project of the Nigerian government.

Table 8.1. Summary of research hypothesis and findings

Problem statement	Hypothesis	Expectation	Finding	Decision
Chapter 5				
Bank experience affects the efficiency of credit creation (loan and investments).	Hypothesis 1a. Unit cost decreases with cumulative experience in credit creation (loans).	Negative	Negative	Do not reject
	Hypothesis 1b. Unit cost decreases with cumulative experience in credit creation (interest income).	Negative	Negative	Do not reject
Bank experience affects the efficiency of lending to the real sector and service provisions (gross value added to the economy).	Hypothesis 2. Unit cost decreases with cumulative experience in gross value added to the economy.	Negative	Negative	Do not reject
Bank experience affects the efficiency of economic value created (shareholder value created).	Hypothesis 3. Unit cost decreases with cumulative experience in economic value created.	Negative	Positive	reject

Table 8.2. Summary of research questions and findings

Problem statement	Research question	Findings/outcome
Chapter 6		
Diffusion of digital payment technologies in Nigeria	What is the current rate of diffusion of some digital payment technologies in Nigeria?	The four digital financial payment technologies analysed have cumulatively achieved a diffusion rate between 50-60%.
	What is the future trajectory of some digital payment technologies in Nigeria?	Three of the four digital financial technologies analysed were predicted to have achieved 99% diffusion rate between 2027-2030. Mobile digital payment technology was forecasted to achieve 99% diffusion rate by 2040.
Chapter 7		
Challenges, diffusion level, and determinants of electronic banking in Nigeria	What is the adoption/diffusion level of electronic banking in Nigeria?	Electronic banking has achieved at least 80% diffusion rate among a large sample of respondents (N = 1228).
	What are the challenges of electronic banking adoption in Nigeria?	Low acceptance of electronic payment among businesses was due to widespread electronic fraud. Poor digital security infrastructure made users prone to electronic fraud.
	What are the determinants of electronic banking adoption in Nigeria?	Socioeconomic characteristics such as age, gender, employment type, annual income, and proximity to bank branches are determinants of the specific type of electronic platform or services adopted.

8.3. Contribution of the study

The above findings contribute to the literature in three broadways.

First, the theory of organisational learning is applied to banks. This theory has been applied to many organisations but has found limited applications in banks. The analyses here contribute to the debate on how bank experience could contribute to financial development, improve financial performance, and reduce bank failure rate (Barnett et al., 1994; Bush, 2015; Kim et al., 2009; Zollo & Singh, 2004). In particular, both the framework and the research method that applies the learning curve to model bank experience in this research were significant contributions in the context of the organisational learning literature. Another unique contribution is operationalising and defining the unit of experience that allows for empirical estimation of the relationship between unit cost and cumulative output in banks.

Second, the findings of this thesis contribute to the debate on the factors affecting the success of two recent monetary policies viz. the cashless economy and the financial integration strategy of the Nigerian government.

Third, the findings of this thesis also contribute to the debate on the social and economic impact of the proliferation of financial technologies in Nigeria where weak policies, inadequate digital infrastructure, and corporate malpractices have continued to weaken the financial economy.

8.4. Implications and recommendations

The aforementioned findings have some implications for both policy and research.

First, the findings on the learning curve of banks challenge and stimulate further discourse on the role of bank experience on bank productivity. This has implication for further research into how banks, as organisations, learn from experience (learning-by-banking). In practise, the findings are useful to bank managers in their evaluation of cost dynamics in bank credit creation (risk management and lending to the real sector), and to regulators in their evaluation of financially developed, or rather, experienced banks. The lack of positive economic profits created might be a pointer to an underlying issue that must be address. This is because banks must create value to remain in business sustainably.

Therefore, value creation, especially economic value creation, is an important policy item in bank production and policy strategy that identifies value creation metrics be introduced and implemented in Nigeria's DMBs.

Second, the findings on the forecast of EPS, which identified mobile payment system as the most diffused platform going forward, have huge economic implications for Nigeria as a fast-growing economy with an expanding financial sector. However, the successful diffusion of the mobile payment system over its lifecycle relies on strong policy thrusts from regulators that can ensure a sustainable, secure, and efficient mobile payment system.

Lastly, the presence of widespread electronic fraud due to poor digital financial security infrastructure is a barrier to achieving a sustainable cashless policy, financial inclusion, and financial development in Nigeria. These should be addressed by (a) continuous deployment of safe e-banking platforms and services enabled by strong policy consolidation that protects users against all forms of electronic fraud, and (b) aggressive digital infrastructure upgrade and commitment from banks, service providers, and regulators that must be pursued to restore confidence among e-banking users.

8.5. Limitations and future direction

This study has a few limitations. First, operationalising bank experience is tricky because there is no standard definition of the unit of service in banks. Furthermore, outputs in banks have many dimensions. Future research could explore other bank outputs that improve with bank experience.

Second, in the empirical model, the price of capital was estimated using a negative derivative of a full translog cost function, in line with past studies. This is an alternative to using the Capital Asset Pricing Model (CAPM) for estimating the price of capital for listed banks. This alternative approach is believed to provide a good measure for the opportunity cost of capital, since not all banks are usually listed. Notably, this estimation has a direct impact on how 'economic value added' is calculated. Future studies could dwell on a large sample of listed banks where the CAPM could be used to estimate the cost of capital.

References

- Acha, I. (2008). Electronic banking in Nigeria: concept, challenges and prospoeet. *International Journal of Development and Management Review*, 3(1), 1–15.
- Adamuthe, A. C., & Thampi, G. T. (2019). Technology forecasting: A case study of computational technologies. *Technological Forecasting and Social Change*, 143(March), 181–189. <https://doi.org/10.1016/j.techfore.2019.03.002>
- Adegbaju, A. A., & Olokoyo, F. O. (2008). Recapitalization and Banks ' Performance : A Case Study of Nigerian Banks. *African Economic and Business Review*, 6(1), 1–17.
- Adeleke, A. (2014). *The Informal Financial Markets in Nigeria*.
[https://www.cbn.gov.ng/out/2016/mpd/understanding monetary policy series no 43.pdf](https://www.cbn.gov.ng/out/2016/mpd/understanding%20monetary%20policy%20series%20no%2043.pdf)
- Adewuyi, I. D. (2011). Electronic banking in Nigeria: challenges of the regulatory authorities and the way forward. *International Journal of Economic Development Research and Investment*, 2(1), 149–156.
- Adu, A. C. (2016). Cashless policy and its effects on the nigerian economy. *European Journal of Business, Economic and Accountancy*, 4(2), 81–88.
- Aduba, J. J., & Asgari, B. (2020). Productivity and technological progress of the Japanese manufacturing industries, 2000–2014: estimation with data envelopment analysis and log-linear learning model. *Asia-Pacific Journal of Regional Science*, 4(2), 343–387. <https://doi.org/10.1007/s41685-019-00131-w>
- Aduba, J. J., & Izawa, H. (2020). Economy-wide Learning: A Comparative Study of Manufacturing and Non-manufacturing Sectors in Japan. In *Emerging Issues and Development in Economics and Trade. Vol.4* (1st editio, pp. 1–16). Book Publisher International. <https://doi.org/10.9734/bpi/eidet/v4>
- Agboola, A. A. (2003). Impact of Electronic Banking on Customer Services in Lagos, Nigeria. *Journal of Social Sciences*, 7(1), 27–36.
<https://doi.org/10.1080/09718923.2003.11892321>
- Agwu, M., & Carter, A.-L. (2014). Mobile Phone Banking In Nigeria: Benefits, Problems and Prospects. *International Journal of Business and Commerce*, 3(6), 50–70.

- Ajiboye, O., Kalejaiye, O., & Dada, O. (2013). Electronic Payments and Economic Growth in Nigeria. In *RTC Advisory Services Ltd* (Issue June).
- Akujinma, A. F., Chijindu, A. A., & Theodora, O. N. (2017). An Empirical Assessment of the Impact of Commercial Banks' Lending on Economic Development of Nigeria. *International Journal of Applied Economics, Finance and Accounting*, 1(1), 14–29. <https://doi.org/10.33094/8.2017.11.14.29>
- Argote, L. (2012). Organizational Learning Curves: Overview. In *Organizational Learning: Creating, Retaining and Transferring Knowledge* (2nd editio, pp. 10–11). Springer Science and Business Media LLC.
<https://doi.org/10.4135/9781412952613.n372>
- Argote, L., & Ingram, P. (2000). Knowledge transfer: A basis for competitive advantage in firms. *Organizational Behavior and Human Decision Processes*, 82(1), 150–169. <https://doi.org/10.1006/obhd.2000.2893>
- Arrow, K. J. (1962). The Economic Implications of Learning by Doing. *The Review of Economic Studies*. <https://doi.org/10.2307/2295952>
- Asgari, B., & Yen, L. W. (2009). Accumulated knowledge and technological progress in terms of learning rates: A comparative analysis of the manufacturing industry and the service industry in Malaysia. *Asian Journal of Technology Innovation*.
<https://doi.org/10.1080/19761597.2009.9668674>
- Atanda, A. A., & Alimi, O. Y. (2012). Anatomy of Cashless Banking in Nigeria: What Matters? *Munich Personal RePEc Archive, MPRA Paper*(1–22).
- Avilés, J. M., Larghi, S. B., & Aguayo, M. A. M. (2016). The informational life of the poor: A study of digital access in three Mexican towns. *Telecommunications Policy*, 40(7), 661–672. <https://doi.org/10.1016/j.telpol.2015.11.001>
- Badiru, A. B. (1992). Computational Survey of Univariate and Multivariate Learning Curve Models. *IEEE Transactions on Engineering Management*.
<https://doi.org/10.1109/17.141275>
- Bahk, B., & Gort, M. (1993). Decomposing Learning by Doing in New Plants. *Journal of Political Economy*. <https://doi.org/10.1086/261888>
- Balasubramanian, N., & Lieberman, M. B. (2010). Industry learning environments and the heterogeneity of firm performance. *Strategic Management Journal*, 31, 390–412. <https://doi.org/10.1002/smj.816>

- Bankole, F. O., Bankole, O. O., & Brown, I. (2011). Mobile Banking Adoption in Nigeria. *The Electronic Journal of Information Systems in Developing Countries*, 47(1), 1–23. <https://doi.org/10.1002/j.1681-4835.2011.tb00330.x>
- Barnett, W. P., Greve, H. R., & Park, D. Y. (1994). An evolutionary model of organizational performance. *Strategic Management Journal*, 15, 11–28.
- Baum, J. A. C., & Ingram, P. (1998). Survival-enhancing learning in the Manhattan Hotel Industry, 1898-1980. *Management Science*, 44(7), 996–1016. <https://doi.org/10.1287/mnsc.44.7.996>
- Berger, A. N., & Humphrey, D. B. (1992). Measurement and Efficiency Issues in Commercial Banking. In *Output Measurement in the Service Sectors* (Ed, Issue January, pp. 245–300). University of Chicago Press. <http://ideas.repec.org/h/nbr/nberch/7237.html>
- Besanko, D., Dranove, D., Shanley, M., & Schaefer, S. (2013). The horizontal boundaries of the firm. In *Economics of Strategy* (6th ed., pp. 61–93). Wiley.
- Bhargava, S. C. (1995). A generalized form of the fisher-pry model of technological substitution. *Technological Forecasting and Social Change*, 49(1), 27–33. [https://doi.org/10.1016/0040-1625\(95\)00004-T](https://doi.org/10.1016/0040-1625(95)00004-T)
- Bhasin, M. L. (2013). Economic Value Added and Shareholders' Wealth Creation: Evidence from a Developing Country. *International Journal of Finance and Accounting*. <https://doi.org/10.5923/j.ijfa.20130204.01>
- Boone, T., & Ganeshan, R. (2001). The effect of information technology on learning in professional service organizations. *Journal of Operations Management*, 19(4), 485–495. [https://doi.org/10.1016/S0272-6963\(00\)00064-4](https://doi.org/10.1016/S0272-6963(00)00064-4)
- Bush, G. (2015). Learning by Banking: Testing for Experience Effects in the Financial Sector. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.2688578>
- C. Ezeamama, M., Ndubuisi, N. J., I. Marire, D. (Mrs) M., & Mgbodile, D. C. . (2014). The Impact of Central Bank of Nigeria Cashless Policy in Nigeria Economy. *IOSR Journal of Business and Management*, 16(12), 84–95. <https://doi.org/10.9790/487x-161218495>
- CBN. (2004). *CBN Briefs*. [https://www.cbn.gov.ng/OUT/PUBLICATIONS/REPORTS/RD/2007/CBN BRIEFS 2004-2005 EDITION.PDF](https://www.cbn.gov.ng/OUT/PUBLICATIONS/REPORTS/RD/2007/CBN%20BRIEFS%202004-2005%20EDITION.PDF)

- CBN. (2010). *Payments System Transformation: Cash-less Nigeria Implementation*.
[https://www.cbn.gov.ng/cashless/New Payment Systems.pdf](https://www.cbn.gov.ng/cashless/New%20Payment%20Systems.pdf)
- CBN. (2011). *Further Clarifications on Cash-Less Lagos Project*.
[https://www.cbn.gov.ng/out/2011/pressrelease/gvd/cashless lagos brief for website revised2.pdf](https://www.cbn.gov.ng/out/2011/pressrelease/gvd/cashless%20lagos%20brief%20for%20website%20revised2.pdf)
- CBN. (2014). *Phase III nationwide rollout of the cashless policy; extension to 30 remaining states*. <https://www.cbn.gov.ng/out/2014/ccd/cashless-rollout.pdf>
- CBN. (2017a). *Circular on nationwide implementation of the cashless policy*.
<https://www.cbn.gov.ng/Out/2017/CCD/circular23022017.pdf>
- CBN. (2017b). The Nigerian Financial System at a Glance. In *CBN, Monetary Policy department*. [https://www.cbn.gov.ng/Out/2017/CCD/THE NIGERIAN FINANCIAL SYSTEM.pdf](https://www.cbn.gov.ng/Out/2017/CCD/THE%20NIGERIAN%20FINANCIAL%20SYSTEM.pdf)
- CBN. (2018a). *Central bank of nigeria annual report 2018*.
[https://www.cbn.gov.ng/Out/2019/RSD/2018 AR KAMA1.pdf](https://www.cbn.gov.ng/Out/2019/RSD/2018%20AR%20KAMA1.pdf)
- CBN. (2018b). *Exposure draft of the national financial inclusion strategy refresh*.
[https://www.cbn.gov.ng/Out/2018/CCD/Exposure Draft of the National Financial Inclusion Strategy Refresh_July 6 2018.pdf](https://www.cbn.gov.ng/Out/2018/CCD/Exposure%20Draft%20of%20the%20National%20Financial%20Inclusion%20Strategy%20Refresh_July%206%202018.pdf)
- CBN. (2019). *Regulation on electronic payments and collections for public and private sectors in Nigeria*. [https://www.cbn.gov.ng/Out/2019/PSMD/Regulation on Electronic Payments and Collections.pdf](https://www.cbn.gov.ng/Out/2019/PSMD/Regulation%20on%20Electronic%20Payments%20and%20Collections.pdf)
- Clementina, K., & Isu, H. O. (2014). Nigeria's 2005 bank recapitalisation: an evaluation of effects and social consequences. *African J. of Accounting, Auditing and Finance*, 3(4), 245. <https://doi.org/10.1504/ajaaf.2014.069842>
- Darr, E. D., Argote, L., & Eppler, D. (1995). The Acquisition, Transfer, and Depreciation of Knowledge in Service Organizations: Productivity in Franchises. *Management Science*. <https://doi.org/10.1287/mnsc.41.11.1750>
- Devezas, T. C. (2005). Evolutionary theory of technological change: State-of-the-art and new approaches. *Technological Forecasting and Social Change*, 72(9), 1137–1152. <https://doi.org/10.1016/j.techfore.2004.10.006>
- Drake, L., Hall, M. J., & Simper, R. (2006). The Impact of Microeconomic and Regulatory Factors on Bank Efficiency; A non-parametric Analysis of Hong Kong's Banking System. *Journal of Banking and Finance*, 30, 1443–1466.

- Eburajolo, C. O., & Aisien, L. N. (2019). Impact of Commercial Banks' Credit to the Real Sector on Economic Growth in Nigeria. *Oradean Journal of Business and Economics*, 4(1), 5–10.
- Egelman, C. D., Epple, D., Argote, L., & Fuchs, E. R. H. (2017). Learning by doing in multiproduct manufacturing: Variety, customizations, and overlapping product generations. *Management Science*. <https://doi.org/10.1287/mnsc.2015.2352>
- Ene, E. E., Abba, G. O., & Fatokun, G. F. (2019). The Impact of Electronic Banking on Financial Inclusion in Nigeria. *American Journal of Industrial and Business Management*, 09(06), 1409–1422. <https://doi.org/10.4236/ajibm.2019.96092>
- Eugenia, O. N., Scholastica, E. U., & David, E. T. (2018). Commercial Banking and Economic Growth in Nigeria. *Open Journal of Economics and Commerce*, 1(1), 68–75.
- Fan, Y., Chen, J., Shirkey, G., John, R., Wu, S. R., Park, H., & Shao, C. (2016). Applications of structural equation modeling (SEM) in ecological studies: an updated review. *Ecological Processes*, 5(1). <https://doi.org/10.1186/s13717-016-0063-3>
- Fife, E., & Pereira, F. (2016). The promise and reality: Assessing the gap between theory and practice in ICT4D. In *Telecommunications Policy* (Vol. 40, Issue 7, pp. 595–601). Elsevier Ltd. <https://doi.org/10.1016/j.telpol.2016.05.004>
- Fiol, M., & Lyles, M. (1985). Organizational Learning. *Academy of Management Review*, 10(4), 803–813. <https://doi.org/10.31686/ijier.vol7.iss4.1427>
- Fiordelisi, F. (2007). Shareholder value efficiency in European banking. *Journal of Banking and Finance*. <https://doi.org/10.1016/j.jbankfin.2006.10.021>
- Fiordelisi, F., & Molyneux, P. (2010). The determinants of shareholder value in European banking. *Journal of Banking and Finance*. <https://doi.org/10.1016/j.jbankfin.2009.11.018>
- Gillwald, A., Odufuwa, F., & Mothobi, O. (2018). *The state of the ICT in Nigeria*. <https://researchictafrica.net/after-access-nigeria-state-of-ict-2017/>
- Greene, W. H. (2012). Econometric Analysis. In Intergovernmental Panel on Climate Change (Ed.), *Prentice Hall* (7th Editio). Cambridge University Press. <https://doi.org/10.1017/CBO9781107415324.004>
- Grigorian, D. A., & Manole, V. (2006). Determinants of Commercial Bank

- Performance in Transition: An Application of Data Envelopment Analysis. *Comparative Economic Studies*, 48, 497–522.
- GSM. (2019). *The mobile economy, West Africa*.
<https://www.gsma.com/subsaharanafrica/resources/the-mobile-economy-sub-saharan-africa-2019#:~:text=Sub-Saharan Africa will remain,representing around half the population.>
- Gujarati, D. (2004). *Basic Econometrics* (4th Editio). McGraw-Hill.
- Huber, C. (2013). Generalized Structural Equation Modeling Using Stata. In *Italian Stata Users Group Meeting*.
http://www.stata.com/meeting/italy13/abstracts/materials/it13_huber.pdf
- Hughes, J., & Mester, L. J. (2014). Measuring the Performance of Banks: Theory, Practice, Evidence, and Some Policy Implications. In *The Oxford Handbook of Banking* (2nd ed.). Oxford University Press.
<https://doi.org/10.1093/oxfordhb/9780199688500.013.0010>
- Hughes, J. P., Mester, L. J., & Moon, C. G. (2001). Are scale economies in banking elusive or illusive?: Evidence obtained by incorporating capital structure and risk-taking into models of bank production. *Journal of Banking and Finance*.
[https://doi.org/10.1016/S0378-4266\(01\)00190-X](https://doi.org/10.1016/S0378-4266(01)00190-X)
- IMF and World Bank. (2018). The Bali Fintech Agenda - Chapeau Paper. *World Bank*, 1–36.
- Innocent, I. O., Ademola, O. G., & Glory, E. W. (2019). Influence of Bank Credits on the Nigerian Economy. *American Economic & Social Review*, 5(1), 1–9.
<https://doi.org/10.46281/aesr.v5i1.240>
- Irwin, D. A., & Klenow, P. J. (1994). Learning-by-doing spillovers in the semiconductor industry. *Journal of Political Economy*.
<https://doi.org/10.1086/261968>
- ITU. (2019). *Mobile-cellular subscriptions*. <https://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx>
- Jatau, V., & Dung, K. (2014). The Central Bank of Nigeria’s Cashless Policy: A Major Panacea for Eliminating Corruption and Enhancing Sustainable Development in Nigeria. *African Research Review*, 8(4), 198. <https://doi.org/10.4314/afrrrev.v8i4.16>
- John, N. J., Emmanuel, N. C., Ikechi, K. S., & Eke, C. K. (2020). Cashless Policy and

- the Nigerian Payment System. *International Journal of Innovation and Economic Development*, 5(6), 7–28. <https://doi.org/10.18775/ijied.1849-7551-7020.2015.56.2001>
- Joseph, O., & Richard, I. (2015). *Electronic Payment System in Nigeria : Its Economic Benefits and Challenges*. 6(16), 56–63.
- Karaoz, M., & Albeni, M. (2005). Dynamic technological learning trends in Turkish manufacturing industries. *Technological Forecasting and Social Change*. <https://doi.org/10.1016/j.techfore.2004.09.005>
- Kim, J. Y., Kim, J. Y., & Miner, A. S. (2009). Organizational learning from extreme performance experience: The impact of success and recovery experience. *Organization Science*, 20(6), 958–978. <https://doi.org/10.1287/orsc.1090.0439>
- Kimball, R. C. (1998). Economic profit and performance measurement in banking. *New England Economic Review*, 35–53. <https://www.bostonfed.org/publications/new-england-economic-review/1998-issues/issue-july-august-1998/economic-profit-and-performance-measurement-in-banking.aspx>
- Kmenta, J. (1986). *Elements of Econometrics* (2nd ed.). Macmillan.
- Kraja, A., & Braimllari Spaho, A. (2019). Modeling and Forecasting the Diffusion of Mobile Telephony in Albania and Turkey. *Journal of Engineering Technology and Applied Sciences*, January 2020. <https://doi.org/10.30931/jetas.599517>
- Kucharavy, D., & De Guio, R. (2011). Logistic substitution model and technological forecasting. *Procedia Engineering*, 9, 402–416. <https://doi.org/10.1016/j.proeng.2011.03.129>
- Lapr , M. A., & Van Wassenhove, L. N. (2001). Creating and transferring knowledge for productivity improvement in factories. *Management Science*. <https://doi.org/10.1287/mnsc.47.10.1311.10264>
- Lee, C. C., Wang, C. W., & Ho, S. J. (2020). Financial innovation and bank growth: The role of institutional environments. *North American Journal of Economics and Finance*, 53(August 2019), 101195. <https://doi.org/10.1016/j.najef.2020.101195>
- Lee, H. joo, Lee, S., & Yoon, B. (2011). Technology clustering based on evolutionary patterns: The case of information and communications technologies. *Technological Forecasting and Social Change*, 78(6), 953–967. <https://doi.org/10.1016/j.techfore.2011.02.002>

- Levitt, S. D., List, J. A., & Syverson, C. (2013). Toward an understanding of learning by doing: Evidence from an automobile assembly plant. *Journal of Political Economy*. <https://doi.org/10.1086/671137>
- Li, Y., & Li, Y. (2020). Analysis of the Development Process of Payment Methods and Mobile Payment Technology Diffusion Trend in China. *Technology and Investment*, 11(01), 1–11. <https://doi.org/10.4236/ti.2020.111001>
- Lombardi, S., Santini, G., Marchetti, G. M., & Focardi, S. (2017). Generalized structural equations improve sexual-selection analyses. *PLoS ONE*, 12(8), 1–20. <https://doi.org/10.1371/journal.pone.0181305>
- Lotfi, A., Lotfi, A., & Halal, W. (2014). Forecasting technology diffusion : a new generalisation of the logistic model. *Technology Analysis & Strategic Management*, 26(8), 943–957. <https://doi.org/10.1080/09537325.2014.925105>
- Martino, J. P. (2003). A review of selected recent advances in technological forecasting. *Technological Forecasting and Social Change*, 70(8), 719–733. [https://doi.org/10.1016/S0040-1625\(02\)00375-X](https://doi.org/10.1016/S0040-1625(02)00375-X)
- Meade, N., & Islam, T. (2006). Modelling and forecasting the diffusion of innovation - A 25-year review. *International Journal of Forecasting*, 22(3), 519–545. <https://doi.org/10.1016/j.ijforecast.2006.01.005>
- Meyer, P. (1994). Bi-logistic growth. *Technological Forecasting and Social Change*, 47(1), 89–102. [https://doi.org/10.1016/0040-1625\(94\)90042-6](https://doi.org/10.1016/0040-1625(94)90042-6)
- Meyer, P. S., & Ausubel, J. H. (1999). Carrying capacity: A model with logistically varying limits. *Technological Forecasting and Social Change*, 61(3), 209–214. [https://doi.org/10.1016/S0040-1625\(99\)00022-0](https://doi.org/10.1016/S0040-1625(99)00022-0)
- Meyer, P. S., Yung, J. W., & Ausubel, J. H. (1999). A Primer on Logistic Growth and Substitution. *Technological Forecasting and Social Change*, 61(3), 247–271. [https://doi.org/10.1016/s0040-1625\(99\)00021-9](https://doi.org/10.1016/s0040-1625(99)00021-9)
- Michalakelis, C., Varoutas, D., & Sphicopoulos, T. (2008). Diffusion models of mobile telephony in Greece. *Telecommunications Policy*, 32(3–4), 234–245. <https://doi.org/10.1016/j.telpol.2008.01.004>
- Morrison, T. G., Morrison, M. A., & McCutcheon, J. M. (2017). Best Practice Recommendations for Using Structural Equation Modelling in Psychological Research. *Psychology*, 08(09), 1326–1341.

- <https://doi.org/10.4236/psych.2017.89086>
- Moundigbaye, M., Sea, W., & Reed, R. (2018). Which panel data estimator should I use.pdf. *Economics: The Open-Access, Open-Assessment E-Journal*, 12(2018–4), 1–31. <http://www.economics-ejournal.org/economics/journalarticles/2018-4>
- Muritala, T. A., Ijaiya, M. A., Adekunle, A. O., & Abidoye, M. K. (2018). Capitalization and bank performance: Evidence from Nigerian Banking Sector. *E-Finanse*, 13(4), 67–75. <https://doi.org/10.1515/fiqf-2016-0036>
- National Bureau of Statistics. (2020). Nigerian Gross Domestic Product Report Quarter Two. In *National Bureau of Statistics Quarterly Report, 2020* (Issue 03). <http://www.nigerianstat.gov.ng/nanapages/download/329>
- NeFF. (2016). *A Changing Payments Ecosystem : the Security Challenge*. [https://www.cbn.gov.ng/Out/2017/CCD/A CHANGING PAYMENTS ECOSYSTEM NeFF 2016 Annual Report.pdf](https://www.cbn.gov.ng/Out/2017/CCD/A%20CHANGING%20PAYMENTS%20ECOSYSTEM%20NeFF%202016%20Annual%20Report.pdf)
- Nguena, C.-L. (2019). On financial innovation in developing countries: The determinants of mobile banking and financial development in Africa. *Journal of Innovation Economics*, n°29(1), 69. <https://doi.org/10.3917/jie.029.0069>
- NIBSS. (2019). *E-Payments Fact Sheet for Jan-Dec 2019*. <https://nibss-plc.com.ng/epayment-fact-sheet/>
- Obaigbona, E. C. (2010). *Regulatory framework for mobile payments services in Nigeria*. <https://www.efina.org.ng/wp-content/uploads/2018/12/Mobile-Payments-Dissemination-WorkshopCBN-E-Obaigbona-Presentation.pdf>
- Okeke, T., Ezech, G., & Ugochukwu, N. (2015). Service Quality Dimensions and Customer Satisfaction with Online Services of Nigerian Banks. *The Journal of Internet Banking and Commerce*, 20(3), 1–23. <http://www.icommercecetral.com/open-access/service-quality-dimensions-and-customer-satisfaction-with-online-services-of-nigerian-banks.php?aid=60222>
- Olasina, G. (2015). Factors influencing the use of M-banking by academics: case of SMS-based M-banking. *The African Journal of Information Systems*, 7(4).
- Oluwatolani, O., Joshua, A., & Philip, A. (2011). *The Impact of Information Technology in Nigeria's Banking Industry*. 7(2), 63–67. <http://arxiv.org/abs/1108.1153>
- Ozili, P. K. (2018). Impact of digital finance on financial inclusion and stability. *Borsa Istanbul Review*, 18(4), 329–340. <https://doi.org/10.1016/j.bir.2017.12.003>

- Paradi, J. C., & Zhu, H. (2013). A survey on bank branch efficiency and performance research with data envelopment analysis. *Omega (United Kingdom)*, 41(1), 61–79. <https://doi.org/10.1016/j.omega.2011.08.010>
- Parks, R. W. (1967). Efficient Estimation of a System of Regression Equations when Disturbances are Both Serially and Contemporaneously Correlated. *Journal of the American Statistical Association*. <https://doi.org/10.1080/01621459.1967.10482923>
- Pazarbasioglu, C., Mora, A. G., Uttamchandani, M., Natarajan, H., Feyen, E., & Saal, M. (2020). *DIGITAL FINANCIAL SERVICES April 2020*. April.
- Plaza, M., Ngwenyama, O. K., & Rohlf, K. (2010). A comparative analysis of learning curves: Implications for new technology implementation management. *European Journal of Operational Research*, 200(2), 518–528. <https://doi.org/10.1016/j.ejor.2009.01.010>
- Pramongkit, P., Shawyun, T., & Sirinaovakul, B. (2000). Analysis of technological learning for the Thai manufacturing industry. *Technovation*, 20(4), 189–195. [https://doi.org/10.1016/S0166-4972\(99\)00125-X](https://doi.org/10.1016/S0166-4972(99)00125-X)
- Pramongkit, P., Shawyun, T., & Sirinaovakul, B. (2002). Productivity growth and learning potentials of Thai industry. *Technological Forecasting and Social Change*, 69(1), 89–101. [https://doi.org/10.1016/S0040-1625\(99\)00088-8](https://doi.org/10.1016/S0040-1625(99)00088-8)
- Rabe-Hesketh, S., Skrondal, A., & Pickles, A. (2004). Generalized Multilevel Structural Equation Modeling. *Springer Handbooks*, 69(2), 167–190. https://doi.org/10.1007/978-1-84628-288-1_38
- Radić, N. (2015). Shareholder value creation in Japanese banking. *Journal of Banking and Finance*. <https://doi.org/10.1016/j.jbankfin.2014.09.014>
- Ralli, P., Panas, A., Pantouvakis, J., & Karagiannakidis, D. (2020). *Investigation and Comparative Analysis of Learning Curve Models on Construction Productivity : The Case of Caisson Fabrication Process*. 10(3), 219–230. <https://doi.org/10.2478/jeppm-2020-0024>
- Ramanarayanan, S. (2011). Does Practice Make Perfect: An Empirical Analysis of Learning-by-Doing in Cardiac Surgery. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.1129350>
- Reed, W. R., & Ye, H. (2011). Which panel data estimator should I use? *Applied*

- Economics*, 43(8), 985–1000. <https://doi.org/10.1080/00036840802600087>
- Ryu, J., & Byeon, S. C. (2011). Technology level evaluation methodology based on the technology growth curve. *Technological Forecasting and Social Change*, 78(6), 1049–1059. <https://doi.org/10.1016/j.techfore.2011.01.003>
- Senyo, P. K., & Osabutey, E. L. C. (2020). Unearthing antecedents to financial inclusion through FinTech innovations. *Technovation*, March, 102155. <https://doi.org/10.1016/j.technovation.2020.102155>
- Sharma, D., Sharma, A. K., & Barua, M. K. (2013). Efficiency and productivity of banking sector: A critical analysis of literature and design of conceptual model. *Qualitative Research in Financial Markets*, 5(2), 195–224. <https://doi.org/10.1108/QRFM-10-2011-0025>
- Stata. (2018). *Methods and formualars for GSEM* (No. 16; pp. 1–20). Stata Corp. <https://www.stata.com/manuals/semmethodsandformulasforgsem.pdf#semMethodsandformulasforgsem>
- Taiwo, J. N., & Agwu, M. E. (2017). The Role of E-Banking on Operational Efficiency of Banks in Nigeria. *Basic Research Journal of Business Management and Accounts*, 6(January), 1–10. <https://doi.org/10.2139/ssrn.3122498>
- Tarhini, A., Mgbemena, C., Trab, M., & Masa'deh, R. (2015). User Adoption of Online Banking in Nigeria : A Qualitative Study. *Journal of Internet Banking and Commerce*, 17(3), 1–20. <https://doi.org/10.4172/1204-5357.1000132>
- Ugwu, L. O., Oyeibisi, T. O., Ilori, M. O., & Adagunodo, E. R. (2000). Organizational impact of information technology on the banking and insurance sector in Nigeria. *Technovation*, 20(12), 711–721. [https://doi.org/10.1016/S0166-4972\(00\)00013-4](https://doi.org/10.1016/S0166-4972(00)00013-4)
- Umoren, A., & Olokoyo F. (2007). Merger and acquisition in Nigeria: Analysis of performance pre-and-post consolidation. *Lagos Journal of Banking Finance & Economic*, 1(1), 1–16.
- Uyemura, D. G., Kantor, C. C., & Pettit, J. M. (1996). EVAR for banks: Value creation, risk management, and profitability measurement. *Journal of Applied Corporate Finance*. <https://doi.org/10.1111/j.1745-6622.1996.tb00118.x>
- V. Coates, M. Farooque, R. Klavans, K. Lapid, H. Linstone, C. Pistorius, and A. P. (2001). On the future of technological forecasting. *Technological Forecasting and Social Change*, 67, 1–17. [https://doi.org/10.1016/0040-1625\(89\)90009-7](https://doi.org/10.1016/0040-1625(89)90009-7)

- Westland, J. C. (2015). An introduction to structural equation models. *Studies in Systems, Decision and Control*, 22, 1–8. https://doi.org/10.1007/978-3-319-16507-3_1
- Wickens, M. R., & Kmenta, J. (1972). Elements of Econometrics. *Economica*. <https://doi.org/10.2307/2552662>
- Windarto, W., Eridani, E., & Purwati, U. D. (2018). A new modified logistic growth model for empirical use. *Communication in Biomathematical Sciences*, 1(2), 122. <https://doi.org/10.5614/cbms.2018.1.2.5>
- Wolbers, J. J. A. (2017). *Financial technologies paving a bright new path for the world's unbanked population*. 1–53. www.apjii.or.id
- Yao, M., Di, H., Zheng, X., & Xu, X. (2018). Impact of payment technology innovations on the traditional financial industry: A focus on China. *Technological Forecasting and Social Change*, 135(February 2017), 199–207. <https://doi.org/10.1016/j.techfore.2017.12.023>
- Young, P. (1993). Technological growth curves. A competition of forecasting models. *Technological Forecasting and Social Change*, 44(4), 375–389. [https://doi.org/10.1016/0040-1625\(93\)90042-6](https://doi.org/10.1016/0040-1625(93)90042-6)
- Zollo, M., & Singh, H. (2004). Deliberate learning in corporate acquisitions: Post-acquisition strategies and integration capability in U.S. bank mergers. *Strategic Management Journal*, 25(13), 1233–1256. <https://doi.org/10.1002/smj.426>