LEICESTER CASTLE BUSINESS SCHOOL

Essays on Interbank Market Funding, Bank Conduct and Performance in the UK

A thesis submitted in accordance with the requirements of De Montfort University, Leicester, for the award of the degree of Doctor of Philosophy (PhD)

by

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Abstract

The growing importance of interbank money markets, which allows banks to transact among themselves using various financial instruments that cover maturities spanning one day to one year, have been blamed for the systemic exposures that emanated due to the 2007-09 global financial crisis (Georg, 2013; Lucchetta, 2015). As competitive and liquidity pressures increased, several regulatory frameworks were enacted by regulatory authorities to safeguard the banking sector (Afonso et al., 2019). However, practically, banks are performance-driven institutions (Acharya, 2009). Given their distinct business models, objectives and regulatory constraints, they continued to assume higher risks by circumventing the new regulations towards achieving their performance and revenue goals. In some cases, these banks resorted to anti-competitive conducts by grouping together (collusion) and/or merging (monopolization) to deliberately manipulate the benchmark interbank rate and/or their true earnings position (opacity), and using various financial instruments to obtain mutual benefits that lead to cost savings and increased profits (Schrimpf and Sushko, 2019). In light of this, the overall aim of this thesis is to bridge the gap between interbank funding decision and bank's strategic choices such as risk exposure and conduct, and whether the choice of bank business model drives a bank's decision to manage their financial statements to smooth earnings.

To address the overall objective, the thesis is segregated into three empirical essays, presented as chapters to address three key objectives. The first essay covers objective one which focuses on investigating the importance of bank risk exposures through interbank funding on bank efficiency levels. Although unsecured interbank markets enable banks to lend or borrow funds towards achieving their performance objectives, it also exposes banks to various risks which trigger changes in bank risk management and performance. To gain more insights about these linkages and design a comprehensive performance measure, Chapter 2 conceptualizes the overall bank performance management process as a multi-stage process using a three-stage network data envelopment analysis framework with feedback and alliance. The findings suggest that overall bank performance management is achieved via a complement of good alliance between risk and funding, and financial performance. Also, high financial or overall performance may not imply better risk management or allied process performance. Rather, banks are inherently performance driven institutions whose performance objectives are independently optimal

but aggregately suboptimal. Hence, most banks will opt for superior performance outcomes at the expense of sophisticated risk management.

The second essay examines the second objective: whether a concentrated interbank market stimulates anti-competitive bank conduct – i.e. bank collusion or monopolistic pricing, towards enhancing performance. To advance knowledge and understanding on the structure–conduct–performance paradigm within the interbank context, Chapter 3 adopts an approach that incorporates the role of bank conduct in the structure-conduct-performance nexus to offer a valid confirmation of hypothesis. The findings show that interbank market structure provides a channel for banks to collude and engage in monopolistic pricing in the market for bank and business loans, to consequently increase bank performance. This therefore provides support for the validity of the SCP hypothesis in an interbank context. Further, collusion and other anti-competitive behaviours in the interbank market exacerbate incentives for foreign and conglomerate bank entry. Large bank boards are also more likely to behave anti-competitive given their access to greater information, expertise, connections/affiliations and resources.

The third essay, which examines the third objective, provides evidence on the impact of bank business model strategies - retail-oriented, wholesale-oriented, and diversified, on the degree of bank's earnings opacity in the UK. Chapter 4 employs two alternative approaches: (i) explaining earnings opacity directly through the individual bank characteristics, (ii) using the common factors based on the factor analysis to capture inherent latent strategies of business models. To explore the business model effects, the chapter explicitly distinguishes between short-term (within) and long-term (between) effects. The findings suggest that that retail-oriented business models decrease the likelihood earnings management practices in the short-term but not over the long-term. However, wholesale-oriented business models increase the probability of earnings manipulation both in the short- and long-term. Also, while bank business models characterised by greater degree of functional diversification are likely to lower earnings manipulation in the short-term, the long-term incentives cannot be mitigated. The study also demonstrates that low failure risk represents an important channel in mitigating the inherent positive business model effect of on earnings management practices activities both in the short- and long-term.

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Declaration

This thesis "ESSAYS ON INTERBANK MARKET FUNDING, BANK CONDUCT AND PERFORMANCE IN THE UK" is submitted in partial fulfilment of the requirements for the degree Doctor of Philosophy at De Montfort University, Leicester.

I hereby declare that this thesis is the original work composed by myself, and that no part of the work has been submitted, either in part or whole, in support of an application for another degree or qualification of this or any other university or other institute of learning.

I confirm that any ideas, data, images or text adopted from the work of others (whether published or unpublished) are fully credited as such within the work and attributed to their originator in the text, references or in footnotes as required by the guidelines of De Montfort University.

Chapter 1

Introduction

1.1. Background and motivation of the thesis

The aftermath of the global financial crisis in 2007-09 and its adverse consequences on global banking and financial systems has birthed an increasing call for research that addresses the vulnerability and systemic importance of banking and financial frameworks. In the United Kingdom (UK), the financial sector which is predominantly dominated by banking institutions accounts for the large share of economic growth and stability, and epitomizes a significantly different taxonomy. This stance is evidenced by rich historical context, dating from the 19th Century with the inception of London as a global financial hub and climaxing after the 2000s to its current status as an indispensable financial center for key activities within the European Union (Springford et al., 2016) and for financial markets globally (Shabani et al., 2015; Moutsianas and Kosmidou, 2016). However, given the rich history and significance of the UK Interbank market and its benchmark rate, the London Interbank Offered Rate (LIBOR) which imperatively underlines short-term interest rates universally (Abrantes-Metz et al., 2012), one of the most notable effects of the financial crisis was the pronounced pressure in the interbank money market, which manifested through a sharp increase in money market rates (McAndrews et al., 2017). In fact, the rates for both unsecured and secured interbank money market lending deviated enormously and consequently froze out large segments of the financial markets, weakened credit supply, and induced a tremendous deterioration in bank (perceived) creditworthiness, and an unbalanced liquidity distribution among financial institutions (Heider et al., 2015; Afonso et al., 2011; Acharya and Merrouche, 2013).

Practically, these systemic exposures highlight the significance of the interbank market in the monetary and payments system of an economy. Specifically, a well-functioning interbank market is crucial for efficient financial intermediation (Wells, 2004). It connects all financial institutions and enables them to exchange capital for purposes of liquidity management (Hatzopoulos et al., 2015). These markets are also amongst the most liquid markets in the financial system. The adequacy of liquidity within an economy and its efficient intermediation through the banking system is critical towards enhancing the soundness of the financial system, and financing real economic growth (Hryckiewicz and Kozłowski, 2018). Therefore, as competitive and liquidity pressures increased, several regulatory interventions were adopted to boost stability in the banking sector (Wheatley 2012; Afonso et al., 2019). However, practically, banks are performance-driven institutions (Acharya, 2009) and so their decisions tend to be independently optimal but aggregately suboptimal (Dubecq et al., 2016). Given the distinctiveness of their business models, objectives and regulatory constraints, some banks continued to assume greater risks by circumventing the new regulations. In some cases, these banks resorted to anti-competitive conducts by grouping together (collusion) and/or merging (monopolization) to deliberately manipulate the benchmark interbank rate and/or their true earnings position (opacity), and using various financial instruments to obtain mutual benefits that lead to cost savings and increased profits (Silva et al., 2016; Schrimpf and Sushko, 2019). Notwithstanding this, empirical evidence on the interplay between the strategic use of interbank market funding, bank conduct and performance is still in its embryonic stage. In the ensuing paragraphs, the study sheds light on this interplay by highlighting the unique impact of the financial crisis on the interbank money markets and the deliberate manipulation of the LIBOR as a result of banks attempting to circumvent the new regulatory standards during and post financial crisis towards enhancing and/or sustaining their reputation, competitiveness and performance (McConnell, 2013; Duffie and Stein, 2015; Coulter et al., 2017).

By the end of 2006, 48 percent of all bank funds in the UK was sourced through wholesale funding (Bank of England FSR, 2007). These consequently made the banks extremely reliant on the interbank market for liquidity. By the summer of 2007, the “first blow in confidence” hit global financial markets (Vickers, 2011), including the UK, culminating in large mark-to-market losses and liquidity strains and consequently economic slowdowns. Following accelerating credit losses and liquidity constraints for US mortgage firm, Countrywide which operated a similar funding model, market speculation sprung out about the survival of Northern Rock. According to Shabani et al., (2015), the Bank of England (BOE) partly contributed to the high uncertainty levels after it declined assistance to Northern Rock[1], following their inability to sell and dispose of securitized loans from their balance sheet during the early parts of the crisis. In fear of these events, UK interbank participants begun deleveraging and hoarding liquidity, extensive dislocation characterized the credit markets whilst asset-backed securities and other leveraged markets effectively shut (Acharya and Merrouche, 2012; Heider et al., 2015). This is a clear evidence of banks responding to changes in the market to adjust their behaviour. Specifically, the prevailing market structure influences the conduct of banks, which consequently affects their performance. On September 14th 2007, Northern Rock's access to long-term funding markets was shut and the bank resorted to seeking assurance of liquidity support from the BOE. Eventually, the BOE, the Financial Services Authority, and Her Majesty's Treasury acknowledged that contagion risks from Northern Rock were adequate to distort economic activities and therefore warrant assistance via the government's role as lender of last resort. Nevertheless, the resultant announcement of the assistance delayed and thus failed to avert the public panic and subsequent bank-run on Northern Rock by retail depositors. Between August 2007 and March 2008, UK based banks wrote off $49 billion on structured credit exposures (Bank of England FSR, 2008). Aggregately, the impact of these prolonged chaos weakened market indicators and operating conditions especially for unprepared firms that designed their business model on the origination and distribution of risk, and consequently increasing the level of systemic uncertainty and pessimism (Bank of England FSR, 2008). In line with these evidences, the notion that the financial network and its structure may influence bank profitability and efficiency is shared across jurisdictions. For instance, Iori et al., (2008) argue that changes in the interbank network structure incentivised banks to increase the number of banks they borrowed funds from but restricted the number of banks they are willing to supply credit to.

[1] A bank established through the demutualization of a building society in 1997. Instead of sourcing its funding through deposits, the business model of the bank rather depended on wholesale funding and balance sheet management via asset securitizations to attain its enormous growth. Within eight years, the bank trebled its market share. By the end of Q2 of 2007, asset securitization of Northern Rock exceeded 17 percent of the aggregate UK Mortgage-Backed Security issuances (i.e., UK's fifth-largest mortgage lender). Ultimately, these issuances were largely dependent on the bank's ability to continue securitizing its mortgages and accessibility to wholesale funding, which proved to be progressively tedious. Moreover, the management of their balance sheet via asset securitizations led to increasing lending spreads (both absolutely and relatively) compared to their competitors.

Among the first empirical studies to postulate theories behind bank failures are Ho and Saunders (1980) and James (1991). From the competition-fragility viewpoint, the literature suggests that competition may induce bank risk taking towards earning higher returns and hence undermine financial stability (Keeley, 1990; Allen and Gale, 2004). Specifically, greater bank competition erodes market power, decreases profit margins, and consequently destroying firm value thus encouraging bank risk taking (Berger et al., 2017). Monopoly (higher degree of market power) rent increases in competitive markets however increase a bank’s value and thus discouraging risk-taking behavior (Fu, Lin and Molyneux, 2014). The competition-stability hypothesis contends that monopoly permits banks to charge higher interest rates, which exacerbate adverse selection and moral hazard effects, increases bank risk and threaten financial stability (Schaeck et al., 2009; Allen et al., 2011). Nevertheless, Fiordelisi and Mare, (2014); Schaeck and Cihák, (2014) and Leroy and Lucotte, (2017) contend that competition enhances financial stability by lessening systemic risk since low competition levels tend to increase the correlation in the risk-taking behavior of banks. In line with the above evidence, Monticini and Ravazzolo (2014) contend that interbank market frictions that resulted from the liquidity crises increased bank’s ability to charge higher intraday interest rate spreads and thus, created the platform for abnormal gains through arbitrage. Similarly, Silva et al., (2016) argue that the core–periphery structure of the interbank market is cost efficient for banks, and thus encourages greater participation of banks in financial networks.

Collectively, these studies reflect the position of the structure-conduct-performance (SCP) hypothesis. Specifically, the SCP paradigm proposes that banks domiciled in concentrated markets will collude to charge higher loan rates, pay lower deposit rates and earn higher profits to boost performance (Mirzaei et al., 2013; Khan et al., 2018). Generally, the banking literature highlights two major hypotheses that underpin the structure-conduct-performance (SCP) relation: the market-power verses the efficient-structure hypothesis, and have implications for competition policies in both the interbank market context and the UK banking system as a whole. By the SCP hypothesis, when a small group of firms dominate a particular market in terms of shares, the likelihood of collusive behaviour amongst these firms increases. Given this greater likelihood, the manifestation of the SCP extends beyond just crisis periods where several unconventional policy measures (e.g., bank consolidations, privatization, deregulation, among others) are enacted by supervisory agencies to safeguard the banking sector (Wheatley 2012; Afonso et al., 2019). Largely, in attempting to meet the complexities of the new and rigorous regulatory and risk management standards, banks resort to repricing the risks associated with their unsecured interbank lending, and thus resulting to higher balance sheet costs (Schrimpf and Sushko, 2019). Moreover, though the new interventions often tend to drive the recovery and stability of the interbank system, it usually facilitates a highly consolidated as well as concentrated market structure (Bech and Monnet, 2016; Afonso et al., 2019).

These regulatory loopholes further create a fertile ground for anti-competitive bank conduct (e.g., collusion and monopolization) as banks continued to group together and use financial instruments to obtain mutual benefits with cost savings and increased profits (Silva et al., 2016). Anti-competitive bank conduct refers to an agreement between two or more banks that is unenforceable in a court of law and aims at enhancing their competitive and/or comparative advantage via collusive and/or monopolistic pricing (Coulter et al., 2017). In the interbank market setting, a clear evidence of anti-competitive bank conduct is the reported collusion by mandated global banks to deliberately manipulate the LIBOR[2] which is calculated using data from "panel banks" responses to a hypothetical question (British Bankers Association, 2018). These responses, however, have no relation to transactional data (i.e., actual market conditions) at the time of submission (Wheatley, 2012). Therefore, exposing the LIBOR to deliberate manipulation by unscrupulous traders and managers of a group global banks mandated for its determination (McConnell, 2013). For transactions that rely on the Libor benchmark to establish borrowing costs, a slight underestimation of the submitted rates may facilitate substantial transfer of wealth between lenders and borrowers (Hall, 2013). As a result, some banks (1) low-balled their borrowing rates primarily to protect their reputation as creditworthy banks, and (2) colluded on their submissions to benefit their derivatives traders by lessening their losses (Abrantes-Metz et al., 2012; Schrimpf and Sushko, 2019).

[2] Thomson Reuters represents the mandated calculation agency for British Bankers Association LIBOR. The LIBOR is utilized as the benchmark for settlement of interest rate contracts on several key futures and options exchanges worldwide and on most Over-the-Counter (OTC) and lending transactions (Corb, 2012; Hall, 2013).

More importantly, the nature of complexity and opacity of modern financial networks and systems poses significant challenges to systemic resilience (Flannery et al., 2013; Anand et al, 2013). Similarly, the level of opacity in the intermediation process creates uncertainty about the inherent risks of banks (Fosu et al., 2018) which may adversely affect the efficiency and stability of bank stock prices (Blau et al., 2017) and consequently result to market inefficiency (Haggard et al., 2008). The extant literature that focuses on systemic risk in credit markets incorporate several dimensions. Whilst one strand of literature examines the link between the network structure of the interbank market and its resilience to the different types of market shocks (Lenzu and Tedeschi, 2012; Georg, 2013), others examined the causes of market contagion by focusing on factors such as asset firesale externalities, roll-overs of risk and portfolio overlaps (Gai et al., 2011; Caccioli et al., 2012; Anand et al., 2013). In particular, research evidence suggests that opacity of bank balance sheet structure may hinder regulation and market discipline of banks in that it restricts the ability of external parties to accurately value and assess their risk-taking propensity (Jungherr, 2018). Indeed, it is argued that the increase in bank regulatory reforms in recent years, such as the comprehensive Basel III framework is driven by the need for greater disclosure, transparency, competition, and more stability of banks (Fosu et al., 2018). Within this literature, scholars highlight that increased complexity in bank business models (Flannery et al. 2013), bank opacity and the resultant increased risk-taking propensity (Jungherr, 2018; Fosu et al., 2018; Mergaerts and Vander Vennet, 2016) were among the factors that fuelled the 2008/09 financial crisis.

It may be conjectured that one fundamental way to address bank opacity, particularly earnings opacity, may be to restrict banks' scope for discretionary accounting choices which enable banks to hold complicated financial assets and postpone the recognition of any expected losses on their balance sheets. However, as far as I am aware, past empirical efforts have virtually given no attention on the effects of bank business model choice on earnings opacity and the incentives to supply high quality accounting information, particularly considering the highly heterogeneous landscape of business model choices available to European banks. More importantly, the recent financial crisis was characterised by aggravated liquidity hoarding due to fear of counterparty risk in the interbank market as bank business models allowed banks to delay and hide disclosure of losses on Asset Backed Securities from credit and liquidity risk (Barrell and Davis, 2008).

These subsequently highlighted the "dark side" of heavy reliance on wholesale (or interbank) funding and consequently triggered the liquidation of banks such as Northern Rock following sudden withdrawals due to negative public signals. Furthermore, although the wholesale funding business model has cues such as the maturity and sourcing, a detailed breakdown of the model is not disclosed in the annual reports (Shin, 2009). This thesis sheds light on how the wholesale funding model compares to its other counterparts, and whether there is an optimal bank business model and a level of failure risk at which earnings opacity is less costly in banking, particularly in the UK. These questions are crucial in the sense that all three constructs (i.e., business model, bank failure and earning opacity) limit bank monitoring and can have extreme cost implications (Bushman and Williams, 2015).

1.2. Objectives of the thesis

The overall aim of this thesis is to bridge the gap between interbank funding decision and bank's strategic choices, and whether the choice of bank business model drives a bank's decision to manage their financial statements to smooth earnings. The contention is that as competitive and liquidity pressures continue to rise to unprecedented levels, banking institutions require new strategies to sustain their performance and ensure survival in the constantly changing financial and economic environment. In fact, Chortareas et al., (2013) contend that banking sector complexity can be attributed to the rise of external and uncontrollable factors which championed key performance interventions and strategies towards enhancing bank profits and stability. In line with these goals, Curi et al. (2015) advocate that refocusing a bank's strategy to emphasize greatly on assets, funding, and income efficiency may represent an effective and efficient banking strategy, particularly for new entrants. Therefore, this thesis seeks to employ recent methodological approaches to provide a coherent knowledge and understanding of a banks' incentives to use interbank funds, and their effects on bank strategic choices (conduct), performance and earnings opacity in the UK.

To address the overall objective, the thesis is segregated into three key empirical essays, presented as chapters. Specifically, three key objectives have been examined in this thesis.

First, *the thesis investigates the importance of bank risk exposures through interbank funding on bank efficiency levels* (Chapter 2). Although extant interbank literature analyzed the relationship between network structure and systemic risk using market interconnectedness or lending relationships (e.g., Anand et al., 2015; Bräuning and Fecht, 2016), the evidence is subject to several unexpected biases such as ignoring the structure of the overall banking system. Moreover, none of these studies use the bank's efficiency to gauge the trading behavior and exposure to risk. Inherently, a bank's ability to perform efficiently is partly dependent on their level of risk taking (Hughes and Mester, 2010). Chapter 2 contends that although unsecured interbank markets enable banks to lend or borrow funds towards achieving their performance objectives, they also expose banks to various risks (e.g., credit and liquidity risk) which trigger changes in bank risk management and performance. To gain more insights about these linkages and design a comprehensive performance measure, the chapter conceptualizes the overall bank performance management process as a multi-stage process with feedback and alliance where the alliance structure captures the endogenous interaction between interbank funding and bank risk. While the European Central Bank (ECB) (2010) defines bank performance as the ability of a bank to remain sustainably profitable, Coffinet and Lin (2010) stresses that bank performance should focus on interventions that will facilitate the identification of bank vulnerabilities particularly regarding bank's profitability. Besides, profitability can serve as early signals of financial distress (Tregenna, 2009). Simply, profits tend to serve as the first line of defense against unexpected losses as well as the key driver of bank capital. Where there are any deficiencies in profit, this may be transmitted to solvency ratios which may consequently weaken the strength of the banking system (Lee and Hsieh, 2013).

A key input to the debate emerged from Hughes and Mester (1998, 2013) who suggests the prerequisite to incorporate bank efficiency as key determinants into the analysis of the nexus between capital and risk levels. Efficient banks, ceteris paribus, may be granted higher capital flexibility or aggregate risk profile by oversight bodies. Conversely, inefficient banks may be induced to assume greater risks as compensation for loses due to moral hazard considerations (Hughes and Mester 1998; 2013). Accordingly, Mirzaei and Moore (2015) suggest that the efficient measurement of bank performance should incorporate a set of measures to signify levels of bank efficiency, profitability and stability. In line with the above, this chapter defines overall bank performance management as a basis or system that enables a bank to continuously monitor and evaluate its operations to determine whether or not objectives are being achieved (Wu et al., 2009; Mirzaei and Moore, 2015). Simply, the chapter conceptualizes the overall bank performance management process as a multi-stage process that incorporate a set of measures that signify levels of bank efficiency, profitability and stability. Specifically, Chapter 2 employs a three-stage network Data Envelopment Analysis (DEA) framework with feedback and alliance to model the inter-temporal relationships among interbank funding, bank risk and efficiency. By adopting the DEA model of performance estimation, the study goes beyond the use of the standard accounting-based or financial indicator methodology (see e.g., Pathan and Faff, 2013; Liang et al., 2013) to incorporate the assumption that a bank is a multi-product firm operating in a highly uncertain and volatile environment and thus, factors in the environment must be incorporated in the analysis. To achieve the above objective, the chapter relies on financial data on individual UK banks from the Orbis Bank Focus database (Bureau Van Dijk) with the panel data spanning an eight-year time period from 2010 to 2017.

Grounded on the above, specific research questions under Chapter 2 include:

i. How is bank performance or efficiency affected by interbank funding liquidity?
ii. Does the decision to use interbank funding expose UK banks to risk exposures and how do banks manage these risks?
iii. What effect does bank risk management (or interbank exposures) have on bank performance or efficiency?
iv. Is it possible to differentiate between banks based on management's ability to effectively manage interbank risk exposures based on the available internal resources?
v. Do international banks have different risk exposures and/or incentives for engaging in interbank business?

Secondly, *the thesis examines whether a concentrated interbank market stimulate bank collusion or monopolistic pricing towards enhancing performance* (Chapter 3). Specifically, the chapter sets out to examine whether the structure of the interbank market influences the behaviour/conducts of banks and ultimately to performance as captured via their profit and cost efficiencies. Rather than employing independent firm specific characteristics, this chapter utilizes market-level conditions to gauge bank-level and interbank performance. Chapter 3 contends that banks engage in financial operations in the interbank market to manage their costs and/or to increase their profits. To achieve performance goals, banks tend to adapt to market changes, which may not necessarily be driven by prior relationships. As such, collusion or monopolistic pricing may ensure that larger banks often have better investment opportunities both within and outside the financial network. To advance knowledge and insight on the SCP within the interbank context, the chapter uses an approach that incorporates the role of bank conduct in the structure-performance nexus to offer a valid confirmation of SCP paradigm. Specifically, Chapter 3 models all three elements in the SCP paradigm (i.e., the structure, the conduct and the performance), a task yet to be achieved by traditional SCP literature (e.g., Weiss and Choi, 2008; Fu and Heffernan, 2009). The panel data used in this chapter was collected from the Orbis Bank Focus database (Bureau Van Dijk) with the data spanning a nine-year time period from 2010 to 2018.

Grounded on the above, specific research questions under Chapter 3 include:

i. Is the SCP hypothesis valid in the context of the UK interbank market?
ii. Does the structure of the interbank market influence the behaviour/conduct of banks?
iii. Does the structure-conduct effect impact bank performance through bank's profit and cost efficiencies?
iv. Does monopoly pricing drive the relationship between interbank market concentration and performance?
v. Are interbank players generating profits through monopolistic pricing?
vi. What are the effects of bank consolidation process, bank ownership, and bank board size on the SCP hypothesis?

The third objective (Chapter 4) focuses on *examining the impact of bank business model strategies on the degree of bank's earnings opacity in the UK*. Specifically, the chapter examines whether the choice of business model drives a bank's decision to manage their financial statements to smooth earnings, circumvent capital requirements, and/or decrease taxes. Chapter 4 contends that the degree of bank's earnings opacity – i.e., how little information there is about the firm's true earnings position or performance (Bhattacharya et al., 2003) and as observed in the case of Northern Rock Bank, is dependent on the choice of bank business model: retail-oriented, wholesale-oriented, and diversified strategy. To achieve this objective, the chapter employs two alternative approaches: (i) explaining earnings opacity directly through the individual bank characteristics, (ii) using the common factors based on the factor analysis to capture inherent latent strategies of business models. Further, to improve understanding and knowledge on the business model effects, Chapter 4 explicitly distinguishes between short-term (within) and long-term (between) effects – temporal stableness vs stableness across banks over time. Further analysis demonstrates that low failure risk (or greater solvency) represents an important channel in mitigating the inherent positive business model effect of on earnings management practices activities. To achieve final objective, the chapter employs a nine-year panel data on individual UK banks collected from the Orbis Bank Focus database (Bureau Van Dijk) and regional data from the UK Office of National Statistics spanning the time period from 2010 to 2018.

Grounded on the above, specific research questions under Chapter 4 include:

i. Do bank business model choices explain earnings opacity in the UK?
ii. Do bank business model choices have a short-term or long-term effect on earnings transparency?
iii. What are the key business model choices available to UK banks?
iv. How does the wholesale funding model compare to the other counterparts?
v. To what extent is the interaction between bank business model and earnings opacity conditional on bank failure risk.
vi. To what extent does accounting rules and reforms and the UK's unique banking structure (i.e., accounting standards, audit qualification and conglomerate-subsidiary effect) affect the business model and earnings opacity nexus?

1.2. Structure of the thesis

The rest of thesis is structured as follows. Chapter 2 discusses and examines the link between interbank funding, bank risk exposure and performance by using a three-stage network DEA approach with feedback and alliance. Chapter 3 looks at the interplay between interbank market structure, bank conduct, and performance, since banks are inherently performance-driven institutions whose profit maximization goal may not only be achieved by minimizing (maximizing) costs (revenues), but also by adapting to market conditions. Chapter 4 discusses whether the degree of bank's earnings opacity is driven by the choice of bank business model. Chapter 5 draws conclusions by reflecting on the contributions, policy implications and directions for future research. Overall, this thesis provides several predictions and insights aimed at enhancing understanding on a banks' incentives for using interbank funds, and their effects on bank conduct, performance and earnings opacity.

Chapter 2

Interbank funding, bank risk exposure and performance in the UK: Evidence from a three-stage network DEA model

2.1. Introduction

A key feature of the recent financial crisis has been the disruption and protracted malfunctioning of interbank markets (Afonso et al., 2011; Acharya and Merrouche, 2012; Heider et al., 2015). The interbank market connects financial intermediaries including banks through a sophisticated network of multilateral exposures where risky activities of financial institutions are financed with borrowed funds (Iori et al., 2008). The interbank literature suggests that aggregate market information and market frictions are the primary causes of poor market functioning. These include information asymmetry (Georg, 2013; Heider et al., 2015), market power (Cai and Thakor, 2008; Acharya et al., 2012), inefficient risk-sharing (Freixas et al., 2011), information contagion (Krainer and Lopez, 2003; Furlong and Williams, 2006; Acharya and Yorulmazer, 2008), bank risk concentration (Curry et al., 2008; Lucchetta, 2015) aggregate liquidity shocks (Allen et al., 2009; Bluhm, 2018) and malfunctioning secondary markets (Diamond and Rajan, 2005; Gorton and Huang, 2004, 2006).

Empirically, studies also show that the risks of network interconnections initiated a sharp reduction in lending among banks which primarily froze out large segments of the financial markets, weakened credit supply, and subsequently caused the global recession (Acharya and Mora, 2015; Affinito and Pozzolo, 2017). The interbank networks and systemic importance evidence also point to the complex web of exposures linking banks' balance sheets (Liu et al., 2017; Benoit et al., 2017), business models (Kok et al., 2016; Hryckiewicz and Kozłowski, 2017), and unequal liquidity distribution amongst banks (Fecht et al., 2011; Hryckiewicz and Kozłowski, 2018) as key causes of the market failure[3]. Irrespective of the extant literature on interbank network structure, lending and exposure, these studies are subject to several shortcomings such as ignoring the structure

[3] The macroeconomic implications of market frictions in interbank markets are examined in Freixas et al., (2000) and Cai et al., (2018).

of the overall banking system. None of these studies uses the bank's efficiency to gauge the trading behavior and exposure to risk. The ability of banks to perform efficiently is partly dependent on their level of risk taking (Hughes and Mester, 2010). Moreover, although theoretical measures of efficiency (e.g., high liquidity and better capitalization) suggest that efficient banks should be less vulnerable, practically these requirements might trigger changes in risk management, cut bank profits and eventually escalate bank risk taking propensity (Chiaramonte and Casu, 2017). Besides, the negative market dynamics which originated and worsened the financial crisis serves as poignant reminder of how individual funding decisions of banks can have a direct impact on bank efficiency, vulnerability and systemic risk.

In this chapter, the study investigates for the first time the nexus between bank efficiency and funding exposure in interbank markets. When overall bank management process is conceptualized as a multi-stage process, this study contend that bank risk is endogenously related to efficiency and emphasize the duality role of risk which is generally overlooked in the evaluation of interbank network risks and contagion. Practically, bank's operations on unsecured interbank markets require compensations for facing the borrowing bank's default risk (credit risk) and the liquidity risk associated to its own future funding requirements. From this viewpoint, risk is an output factor of funding decisions, but from another viewpoint, banks must manage these risks in order to achieve better efficiency and productivity levels. Thus, funding risk plays an integral role as both input and output in interbank lending and incorporating both constitutes to enhancing the resilience of banks and the interbank network. Through the Data Envelopment Analysis (DEA) framework, I formulate a three-stage model with feedback and alliance where the alliance structure explains the endogenous interaction between interbank funding and bank risk. Simply, this study conceptualizes that the overall bank management process as a serially linked three-stage process (interbank funding, risk management and bank performance) encompassing a feedback nexus between funding and efficiency in an interbank setting, and how this nexus is impacted through risk exposure of banking institutions.

The findings suggest that overall bank performance management is achieved via a complement of good alliance between risk and funding, and financial performance. Overall bank performance management is defined as the basis or system that enables a bank to continuously monitor and evaluate its operations to determine whether or not objectives are being achieved (Wu et al., 2009; Mirzaei and Moore, 2015). The findings also show that high financial or overall performance may not imply better risk management or allied process performance. Rather, banks are inherently performance-driven institutions whose performance objectives are independently optimal but aggregately suboptimal. Trading banks can act differently given their business models, objectives and regulatory constraints. Hence, most banks tend to opt for superior performance outcomes (particularly financial) at the expense of sophisticated risk management. These explanations remain remarkably robust regardless of whether the alliance stage or financial performance is given priority in the overall efficiency decomposition. By using the novel resource imbalance index to provide supplementary information on managerial performance, this study shows that bank operations under different levels of risk exposure can be assessed through conditions imposed on the intermediate measures. Simply, I show that it is possible to practically discriminate between equally ranked banks (at any level of performance) based on their ability to effectively manage their internal resources.

Specifically, the chapter contributes to literature in several ways. First, this study extends the contributions of Liu et al. (2017) and Lucchetta (2015), who proposed that endogenous individual bank performance objectives such as efficiency levels are imperative to understanding the evolution and malfunctioning of interbank markets, and whether these individual choices essentially result in a more resilient banking system. Hence, the study contends that banks are practically performance-driven institutions (Acharya, 2009), and their decisions are independently optimal but aggregately suboptimal (Dubecq et al., 2016). Moreover, the approach fulfills a postulate of Delis et al. (2017) that risk and efficiency estimates are endogenous to each other. Theoretically, there is a dual inverse nexus between risk and efficiency. This study extends the banking and finance literature (e.g., Delis et al., 2015; Tsolas and Charles, 2015) by proposing a model that incorporate risk and account for the endogeneity features. Second, the bank efficiency literature focuses predominantly on adopting the two-stage approach with the first stage involving the estimation of efficiency scores and subsequently regressing the scores on independent environmental conditions to mitigate environment bias (e.g., Holod and Lewis, 2011; Sun and Chang, 2011; Paradi et al., 2011). Examining bank performance via a three-stage model is still in its embryonic stage. This chapter builds on the DEA and the two-stage network model with feedback (Liang et al., 2011) and alliance (Galagedera et al., 2018). The three-stage network DEA method with feedback and alliance is used to model the inter-temporal relationships among interbank funding, bank risk and efficiency for UK banks. Third, this chapter provides important information to macroprudential policymakers to develop very close coordination and cooperation with banks to understand their risks, and develop approaches to mitigate them in a sufficiently broad and comprehensive manner. Macroprudential policymakers need to take an international perspective and pay to close attention to potential spillovers and the "spillbacks of the spillovers" from bank risk-taking. The bank lending channel is vital for effective transmission of monetary policy effects to the real economy. Where the banking sector thrives significantly on the operations of foreign banks, monetary policymaking must incorporate relevant dynamics across the global banking market. Moreover, banks need to be trusted as credible managers of the risks they take. The findings from the efficiency analysis will assist bank management decision-making on identifying operational areas that necessitates urgent improvements to support future growth strategies. The coverage of bank performance appraisal in this study is much broader and provides further intuitions to enhance complete understanding of bank production systems.

Lastly, this chapter employs a composite index to examine efficiency in the usage (implied in the model) of internal resources that links multiple stages. The bank performance network representation in this study considers two types of linkages and derive a composite measure to determine efficient internal resource usage in the overall bank performance management process. Extending the application of this index to evaluate internal resource efficiency in other different production models is fairly straightforward. This chapter empirically shows that the internal resource imbalance index may enhance the discriminatory power of performance appraisal via network DEA models where internal resource imbalance is allowed. To the best of my knowledge, this is the first attempt to examine the importance of bank exposure in investigating the link between interbank funding and bank efficiency, by distinguishing between the direct association, and the effect that occurs through each one of the two bank characteristics (risk and financial performance). I investigate these linkages through a novel multi-stage data envelopment analysis model.

The rest of the chapter is organized as follows. Section 2.2 reports a review of the related literature. Section 2.3 describes the data and methodology. Section 2.4 and 2.5 discusses the empirical results and other robustness tests respectively. Section 2.6 offers some conclusions of the chapter.

2.2. Literature review

By the unstable banking hypothesis, large banking networks and institutions tend to encourage riskier activities (e.g., interbank trading) (Shleifer and Vishny, 2010; Boot and Ratnovski, 2016). Moreover, banks prefer short-term funding which consequently increases their vulnerability to generalized liquidity shocks and market failures (Kashyap et al., 2017). Similarly, the agency cost hypothesis argues that banking institutions that engage in complex activities, such as engaging in lending and trading jointly, are more vulnerable to agency problems and poor corporate governance (e.g., Bolton et al., 2007; Laeven and Levine, 2007). Where regulatory authorities are indisposed to closing or unwinding these large and complex banking institutions, this stimulates moral hazard behavior by increasing bank risk taking propensity in anticipation of government bailouts in line with the too-interconnected-to-fail or too-big-to-fail hypothesis (Farhi and Tirole, 2012; Laeven et al., 2016). Despite the theoretical links between network complexities and systemic risk, the empirical literature until now is missing comprehensive tests of whether interbank funding affects bank efficiency, and the extent to which the effect alleviates risk exposure through effective and efficient risk management. The goal of this chapter is to fill these gaps in the literature.

The interbank market plays a key role in the monetary and payments system of an economy and serves to relay essential safety measures for banking and financial institutions (Green et al., 2016). Financial institutions facing the danger of insolvency or illiquidity (e.g., poor cash positions at the close of an operating day) can temporarily cover this shortfall by securing funds (i.e., borrowing) from the central bank, or in the overnight interbank market or through a combination of both (Rochet and Vives, 2004; Garcia-de-Andoain et al., 2016). On the other hand, the interbank market provides an immediate outlet for financial institutions with surplus liquidity or reserves to effectively utilize these reserves by lending out to other institutions that may require funding (Freixas et al., 2004; Müller, 2006; Gallitschke et al., 2017). Acharya et al. (2012) suggests that moral hazard and specific frictions in bank assets lead to interbank frictions. Hence, for a central bank which usually acts as a lender-of-last-resort (under its supervisory role and as a better informed economic agent) to ameliorate this inefficiency, they charge a penalty compared to general market borrowing: an above-market interest rate or additional non-interest costs, or both (Goodhart and Huang, 2005; Garcia-de-Andoain et al., 2016).

Identifying vulnerabilities that may weaken financial system resilience (probably through bank failures) has been an imperative task to financial system oversight bodies and market participants. Regulators strive for timely warning indicators of failures to facilitate the effective and efficient deployment of monitoring resources and to enhance regulatory enforcements. Likewise, market participants (e.g., shareholders and taxpayers) seek to avoid significant resolution costs and to decrease loss resolution times that emanate from failures (Fungacova et al., 2015). Following the recent global financial crisis, extant research focused on utilising bank fundamentals to predict individual and systemic failures. DeYoung and Torna (2013) ascribe the underlying causes of worsening bank conditions and the consequent failures to asset-based nontraditional activities such as venture capital, investment banking and asset securitization. On the other hand, Ng and Roychowdhury (2014) contend that increasing loan loss reserves contribute to subsequent bank failures. Vazquez and Federico (2015) conclude that banking institutions which have weaker structural liquidity and higher leverage have higher chance of failure during crisis, and failure increases with pre-crisis bank risk-taking.

Other studies linked bank exposure to economic conditions in attempting to explain how bank risk is transmitted systemically (Pathan, 2009; Anginer et al., 2018), the impact of regulation on bank risk (Park and Peristiani, 2007; Kashyap et al., 2017), and whether bank risk reduction strategies are evolving through time (Sensama and Jayadev, 2009; Simper et al., 2017). In the process, Paltalidis et al. (2015), and Glasserman and Young (2016) argue that excessive risk-taking leads to bank failures and subsequently having systemic effects on the financial system and economy (see Benoit et al. (2017) for an extensive survey on systemic risk). By probing ownership structure and bank risk during the crisis, Barry et al., (2011) stressed that banks are inherently unstable and thus have a high tendency of taking excessive risk. Moreover, the ownership structure of a bank (i.e., publicly held or privately owned) gives an indication of the distinctiveness of their levels of market discipline and accessibility to capital market.

Imbierowicz and Rauch (2014) suggests that although liquidity risk and credit risk are independent, both can exclusively and jointly contribute to bank failures (Hong et al., 2014). Wagner (2007) and Borio (2014) also suggest that high liquidity buildup or credit growth is an imminent leading indicator of bank crises. Vazquez and Federico, (2015) find that higher funding stability lessens the probability of bank failures. This chapter builds on the above premises to examine whether there is a causal link between the interbank funding, riskiness and efficiency of banks. The chapter focuses on developing a framework that incorporates risk as an endogenous variable into an empirical model of operational efficiency. The interbank funds market represents a key short-term funding alternative amongst financial institutions world-wide. Given that the interbank market is characterized by overnight transactions with very short maturities and lending is unsecured, counterparty risks contribute significantly to interbank funding decisions. Hence, individual participant's characteristics such as efficiency or creditworthiness, and relationships play a key role in determining the premium charged on interbank funds (Craig et al., 2015; Anand et al., 2015; Bräuning and Fecht, 2016).

Extant banking literature has made attempts to identify a variety of measures to describe bank performance. However, practically there exists no generally accepted definition of performance in finance literature. While the European Central Bank (ECB) (2010) defines bank performance as the ability of a bank to remain sustainably profitable, Coffinet and Lin (2010) stresses that bank performance should focus on interventions that will facilitate the identification of bank vulnerabilities particularly regarding bank's profitability. The reason being that, basically profits serve as the first line of defense against unexpected losses as well as the key driver of bank capital (Lee and Hsieh, 2013). Any deficiencies in profit may consequently be transmitted to solvency ratios and eventually weaken the strength of the banking system. Moreover, profitability can serve as early signals of financial distress (Tregenna, 2009). Hence, several empirical papers on bank performance concentrate largely on examining the determinants of bank profitability (Goddard et al., 2004; Athanasoglou et al., 2008; Dietrich and Wanzenried, 2011). On the other hand, Wu et al. (2009) defines bank performance as a basis or system that enables a bank to continuously monitor and evaluate its operations to determine whether or not objectives are being achieved.

Moroever, the limitations of ratio analysis and regression analysis (see, Paradi and Zhu, 2013) also called for the advancement of very robust models for evaluating corporate performance, particularly efficiency. A key input to the debate emerged from Hughes and Mester (1998, 2013) who suggests the prerequisite to incorporate bank efficiency as key determinants into the analysis of the nexus between capital and risk levels. Hughes and Mester (1998, 2013) argues that ceteris paribus, efficient banks may be granted higher capital flexibility or aggregate risk profile by oversight bodies. Conversely, inefficient banks may be induced to assume greater risks as compensation for losses due to moral hazard considerations. Following this argument, some scholarly studies advocate the significance of explicitly recognizing the concept of bank efficiency in empirical models of bank risks (Abid et al., 2018; Bitar et al., 2018). Recent literature has increasingly focused on frontier efficiency or benchmarking analysis to examine the relative efficacy and productivity of decision-making units against the best of other peers or firms within the same business or sector, under similar operating environment and conditions[4]. A key merit for employing the frontier efficiency over other performance measurements dwells on its ability to incorporate economic optimization systems within complex operational environments to produce overall objective numerical efficiency scores ("scale efficiencies" or "X-efficiencies") which are further summarized into a single performance statistic (Korhonen et al., 2001). The frontier efficiency approach has diverse applications in management or corporate governance such as assisting to evaluate whether a firm's performance is improving or worsening relative to a benchmark with regard to scale economies, technology, revenue and profit maximization, and cost minimization (Staub et al., 2010; Fukuyama and Matousek, 2017). The findings from frontier efficiency analysis can support firm management decision making on detecting operational areas that necessitates urgent improvement, setting future growth strategies, identifying productive targets for M&A, among others (Paradi and Zhu, 2013; Kao, 2014). Additionally, it facilitates the determination of attainable targets for inefficient units and

[4] See, for example, Liu et al. (2013) and Emrouznejad and Yang (2018) for a survey and analysis of DEA literature; Aiello and Bonanno, (2018) for a meta-analysis of banking efficiency literature; Sueyoshi et al., (2017) for forty years DEA literature on energy and environment; and Kaffash and Marra, (2017) for DEA citations network analysis of banks, insurance companies and money market funds.

any accompanying impacts of environmental variables (Constantin and Martin, 2009). Hence, providing further intuitions to enhance complete understanding of production systems (Lampe and Hilgers, 2015).

2.3. Data and methodology

2.3.1 Data and sampling

In the empirical investigation, the study population consist of all firms listed on the London Stock Exchange (UK) for which data is available from Orbis Bank Focus database (Bureau Van Dijk). The sample include all banks that have operations on the interbank market and have data spanning over 2010–2017. The Orbis database offers both consolidated and unconsolidated financial statement information, of which this study uses the latter, as it gives an accurate breakdown of the revenue and cost elements. The sample also include foreign banks given that the UK banking system has an enormous domestic presence and operations of foreign banks to match the large-scale global operations of UK banks. This produces a highly homogeneous dataset (in terms of financial services) and ultimately a high level of input-output standardization. Thus, enhancing the comparability of the sampled banks. Lastly, banks are included only if they are classified as commercial banks in Orbis. Incorporating the above conditions generates a final dataset comprising 93 banks or decision-making units representing 75% of all banks classified as commercial banks in Orbis, and that have operations on the UK interbank market.

2.3.2 Input and output specification

To avoid bias and restrictions on the input–output set, a reasonable balance must be attained. Thus, I adopt the Cooper et al. (2007) "rule of thumb" which specified that the sum of DMUs must exceed thrice the summation of inputs and outputs. Failure of this assumption may weaken the degrees of freedom and discriminatory power of DEA and result to a higher number of "efficient" DMUs. Since the goal or interest in stage 1 focuses on interbank funding (borrowing and lending), the chosen inputs comprise: net interbank fees, capital measured as personnel expenses plus the book value of premises and fixed assets, and total interbank loans to non-financial institutions. In addition to these inputs is the feedback element from the third stage; total interbank loans to financial institutions. This study identifies three outputs to proxy for purchased funds or borrowings from the unsecured interbank market; interbank borrowing, short-term wholesale funding, and long-term wholesale (Huang and Ratnovski, 2011). Added to the inputs is the feedback element from stage 3 to stage 1; total interbank loans to financial institutions.

Post financial crisis, banks devoted greater resources to risk management (Tsolas and Charles, 2015; Jacobs et al., 2016) with risk management becoming core to bank profitability, survival and stability evaluation (Zhou et al., 2019). Hence, stage 2 focuses on incorporating measures to assess interbank risk exposures. All outputs from stage 1 are intermediate inputs to stage 2. To incorporate risk emanating outside the interbank market, I include total deposits proxying for the sum of demand and time deposits from customers and off-balance sheet (OBS) items to proxy for bank's asset management activities (Isik and Hassan, 2002; Aysan et al., 2011). OBS activities signify assets or debts generated through credit, loan commitments, securitization and derivative activities that are not disclosed on the bank's balance sheet (Casu and Girardone, 2005). Technically, these measures constitute a key element of banking business and thus serve as a key source of income (Dong et al., 2016). Hence, they should be incorporated in the analysis of bank risk management to avoid any underestimation of total output (Jagtiani and Khanthavit, 1996; Altunbas et al., 2001).

In terms of outputs, studies employed risk-weighted assets to proxy for bank risk (Delis et al., 2014) and the non-performing loans (NPLs) to proxy for credit risk (Zhou et al., 2019). However, following the specification of the Basel accords, the current study employs the proportion of risk-weighted assets to total assets as a proxy for credit risk. Credit risk denotes the stochastic nature of loss given default, changes in the underlying credit quality and changes in the exposure at default (Drehmann and Nikolaou, 2013). Specifically, the probability that borrowing banks will default over a specific horizon. Risk-weighted assets represent a key gauge for bank asset quality as well as riskiness (Khan et al., 2017). Funding liquidity risk is measured as the proportion of liquid assets to total assets (Demirguc-Kunt and Huizinga, 2004; Radić et al., 2012). Liquidity risk emanates from mismatches between revenues and outlays (Holmström and Tirole, 1998). Had third parties been mandated to collateralize their borrowing, liquidity risk may be avoided. However, practically, market frictions may also render financial institutions illiquid and insolvent (Drehmann and Nikolaou, 2013). Thus, exposing lending banks to counterparty risk. As in Schmitz et al. (2017), this study proxy for overall bank insolvency risk using the Tier 1 capital ratio, computed as Tier 1 capital over risk-weighted assets. This measure is homogeneous across banks and underpins the regulatory capital calibration in international standards. It is arguably the best barometer for measuring the default risk of a bank, and indeed serves that purpose in stress testing exercises.

To model risk into bank performance, all outputs of the risk management stage are intermediate inputs to the performance stage. Loan loss provisions have been used as an additional input to signify bank asset quality (Lee and Hsieh, 2013; Delis et al., 2014). Loan loss provisions echo the investment decisions of management in prior years as well as the aggressiveness of banks' lending decisions (Garel and Petit-Romec, 2017). In terms of output, this study employs four bank performance measures. The return on asset is computed as the ratio of net income to total assets. The ROA is extremely applied in banking studies to measure bank profitability (See: García-Herrero et al., 2009; Berger et al., 2010). It signifies how efficiently banks utilize their assets to generate revenue. Return on equity is used as a proxy for the assessment of the financial return of shareholder's investment (Liang et al., 2013). It is computed as the ratio of net income to equity capital. Following the Basel Accords, I adopt bank capital adequacy to proxy for capital adequacy (and management) (Diamond and Rajan, 2000). This is computed as the ratio of total equity to total assets. Equity capital is computed following the Basel Committee specification as the summation of TIER I (i.e., total equity, retained earnings and other disclosed equity reserves) and TIER II (i.e., undisclosed equity reserves, general provisions, hybrid capital instruments, and subordinated debts) components of bank capital. This broader specification of banks' equity incorporates supplementary items that are generally utilized by banking institutions to enhance their capital above the traditional equity (Fiordelisi et al., 2011). Lastly, the net interest income computed as interest income less interest expense. The study assumes that banks are in a better position to support or lend to other financial institutions based on their performance and risk objectives. Table 2.1 presents the mnemonics and description of all input-output measures used in this chapter.

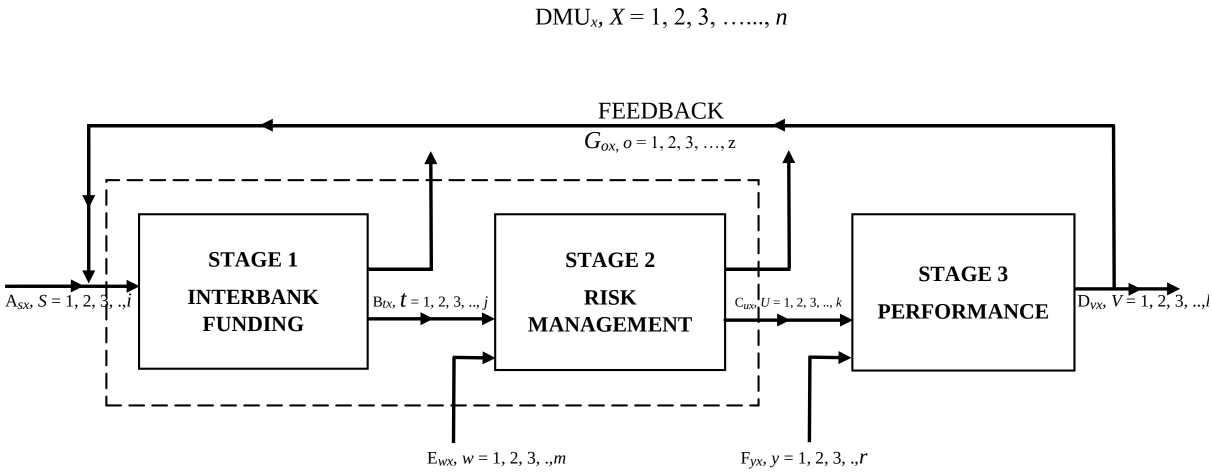
Table 2.1: Summary definition input-output variables.

Usage	Stage 1 – Interbank Funding		Stage 2 – Risk Management		Stage 3 – Performance	
	Variable	**Construction**	**Variable**	**Construction**	**Variable**	**Construction**
Input	Capital (A_{x1})	Personnel expenses plus book value of premises and fixed assets expressed as a percentage	Interbank Borrowing (B_{x1})	Total interbank borrowing from financial institutions expressed as a percentage	Liquidity Risk (C_{x1})	Liquid assets to total assets
	Interbank Fees (A_{x2})	Annual fees paid to financial intermediaries expressed as a percentage	Long-term Wholesale Borrowing (B_{x2})	Total market funds from other financial intermediaries minus liquid assets to total assets.	Credit Risk (C_{x2})	Risk-weighted assets to total assets
	Loans and Advances (A_{x3})	Total interbank loans to non-financial institutions expressed as a percentage	Short-term Wholesale Borrowing (B_{x3})	Total short-term deposits from other financial intermediaries expressed as a percentage.	Solvency Risk (C_{x3})	Tier 1 capital to risk-weighted assets
			Deposits (E_{x1})	Total core deposits to total funding.	Loan Loss (F_{x1})	Loan loss provision to net interest revenues
			OBS (E_{x2})	OBS to risk-weighted assets		
Output	Interbank Borrowing (B_{x1})	Total interbank borrowing from banking institutions expressed as a percentage	Liquidity Risk (C_{x1})	Liquid assets to total assets	Return on Asset (ROA) (D_{x1})	Net income to total assets
	Long-term Wholesale Borrowing (B_{x2})	Total market funds from other financial intermediaries minus liquid assets to total assets.	Credit Risk (C_{x2})	Risk-weighted assets to total assets	Return on Equity (ROE) (D_{x2})	Net income to equity capital
	Short-term Wholesale Borrowing (B_{x3})	Total short-term deposits from other financial intermediaries expressed as a percentage.	Solvency Risk (C_{x3})	Tier 1 capital over risk-weighted assets	Capital Adequacy (D_{x3})	Sum of Tier I & Tier II to total assets
					Net Interest Income (D_{x4})	(Interest income – Interest expense) to total revenue
Feedback	Interbank Lending (G_{x1})	Total interbank loans to financial institutions expressed as a percentage			Interbank Lending (G_{x1})	Total interbank loans to financial institutions expressed as a percentage

2.3.3 Conceptual framework - Three-stage DEA with alliance between stage 1 and stage 2, and feedback variables

This section examines bank performance under various scenarios and discusses where differences exist among banks within the setup. In Figure 2.1, I introduce a serially connected three-stage performance model with alliance between stage 1 and stage 2, and feedback loop between stage 3 and stage 1. Each DMUx (x = 1, 2, 3, ..., n) has s different inputs A_{sx} (s = 1, 2, 3, ..., i) consumed in stage 1 to produce t different outputs B_{tx} (t = 1, 2, 3, ..., j). These t intermediate outputs and w other inputs E_{wx} (w = 1, 2, 3, ..., m) enter stage 2 as inputs to produce u different outputs C_{ux} (u = 1, 2, 3, ..., k). The broken-line rectangle indicates the alliance between stage 1 and stage 2. The u intermediate outputs and y other inputs F_{yx} (y = 1, 2, 3, ..., r) enter stage 3 as inputs to produce two forms of outputs: outputs D_{vx} (v = 1, 2, 3, ..., l) and outputs G_{ox} (o = 1, 2, 3, …, z), that flows cyclically to stage 1 to become partial inputs. These G_{ox} outputs represent the feedback variables. The B_{tx} and C_{ux} account for dual-role variables (Cook et al., 2006; Cook and Zhu, 2007). Distinct from the parametric methodologies, DEA makes no explicit requirements to specify the form of the production function, or the input-output nexus among the variables (Cook et al., 2014).

Figure 2.1: Serially connected three-stage performance model with alliance and feedback



Assessing overall efficiency

Based on the fundamentals of DEA as delineated in Appendix A, the overall efficiency of the three-stage model $e_o^{1,2,3}$ represented in Figure 2.1 is articulated as:

$$e_o^{1,2,3*} = Max \frac{\left(\sum_{t=1}^{j} b_t^{1,2} B_{t0}\right) + \left(\sum_{u=1}^{k} c_u^2 C_{u0}\right) + \left(\sum_{v=1}^{l} d_v D_{v0} + \sum_{o=1}^{z} g_o^3 G_{o0}\right)}{\left(\sum_{s=1}^{i} a_s A_{s0} + \sum_{o=1}^{z} g_o^1 G_{o0}\right) + \left(\sum_{t=1}^{j} b_t^{1,2} B_{t0} + \sum_{w=1}^{m} e_w E_{w0}\right) + \left(\sum_{u=1}^{k} c_u^3 C_{u0} + \sum_{y=1}^{r} f_y F_{y0}\right)} \tag{2.1}$$

Constraint

$$\frac{\sum_{t=1}^{j} b_t^{1,2} B_{tx}}{\sum_{s=1}^{i} a_s A_{sx} + \sum_{o=1}^{z} g_o^1 G_{ox}} \leq 1; \quad a_s, g_o^1, b_t^{1,2} \geq 0$$

$$\frac{\sum_{u=1}^{k} c_u^2 C_{ux}}{\sum_{t=1}^{j} b_t^{1,2} B_{tx} + \sum_{w=1}^{m} e_w E_{wx}} \leq 1; \quad b_t^{1,2}, c_u^2, e_w \geq 0$$

$$\frac{\sum_{v=1}^{l} d_v D_{vx} + \sum_{o=1}^{z} g_o^3 G_{ox}}{\sum_{u=1}^{k} c_u^3 C_{ux} + \sum_{y=1}^{r} f_y F_{yx}} \leq 1; \quad d_v, g_o^3, c_{u,}^3 f_y \geq 0$$

$$c_u^2 \geq c_u^3 \text{ and } g_o^3 \geq g_o^1; \quad u, o = 1,2,3, \dots, u_2;\ o_3$$

The unknown weight vectors of model (2.1) are the vectors of models (A1, A4) and (A6) with $b_t^1 = b_t^2 = b_t^{1,2}$, $t = 1,2,3, \dots, t_{1,2}$ and a set of vectors for the intermediate variables showing the nexus between the allied stages and stage 3. $DMUp, e_o^{1,2,3}$ is said to be completely "efficient" only when $e_o^{1,2,3} = 1$.

Because the current form of model (2.1) is highly non-linear, I develop a more robust form parametric linear program with some parameters by adopting Charnes and Cooper (1962) CCR transformation to change the following variables. Explicitly, let

$$e_o^{1,2,3*} = Max \left(\sum_{t=1}^{j} b_t^{1,2} B_{t0} + \sum_{u=1}^{k} c_u^2 C_{u0} + \sum_{v=1}^{l} d_v D_{v0} + \sum_{o=1}^{z} g_o^3 G_{o0}\right) \tag{2.2}$$

Constraint

$$\sum_{s=1}^{i} a_s A_{s0} + \sum_{o=1}^{z} g_o^1 G_{o0} + \sum_{t=1}^{j} b_t^{1,2} B_{t0} + \sum_{w=1}^{m} e_w E_{w0} + \sum_{u=1}^{k} c_u^3 C_{u0} + \sum_{y=1}^{r} f_y F_{y0} = 1$$

$$\sum_{t=1}^{j} b_t^{1,2} B_{tx} \leq \sum_{s=1}^{i} a_s A_{sx} + \sum_{o=1}^{z} g_o^1 G_{ox}\ ; \quad a_s, g_o^1, b_t^{1,2} \geq 0$$

$$\sum_{u=1}^{k} c_u^2 C_{ux} \leq \sum_{t=1}^{j} b_t^{1,2} B_{tx} + \sum_{w=1}^{m} e_w E_{wx}\ ; \quad b_t^{1,2}, c_u^2, e_w \geq 0$$

$$\sum_{v=1}^{l} d_v D_{vx} + \sum_{o=1}^{z} g_o^3 G_{ox} \leq \sum_{u=1}^{k} c_u^3 C_{ux} + \sum_{y=1}^{r} f_y F_{yx}\ ; \quad d_v, g_o^3, c_u^3 f_y \geq 0$$

$$c_u^2 \geq c_u^3 \text{ and } g_o^3 \geq g_o^1; \quad u, o = 1,2,3, \dots, u_2;\ o_3$$

The optimal efficiency of the three-stage model $e_o^{1,2,3}$ is then articulated using the optimal values of the multipliers of model (2.2)[5]:

$$e_o^{1,2,3*} = \sum_{t=1}^{j} b_t^{1,2*} B_{t0} + \sum_{u=1}^{k} c_u^{2*} C_{u0} + \sum_{v=1}^{l} d_v^{*} D_{v0} + \sum_{o=1}^{z} g_o^{3*} G_{o0} \tag{2.3}$$

Evaluating independent stage-level performance

Step 1: Determining overall DMU_P efficiency

In the model estimation, overall efficiency score is computed as the weighted average efficiency scores of the allied stages and stage 3. Thus, after estimating model (2.2), it is plausible to measure the efficiency scores of the allied stages and stage 3 via substitution using the optimal values of the multipliers produced in model (2.2) in (A8) and subsequently in $e_o^{1,2,3} = W_{1,2} e_o^{1,2} + W_3 e_o^3$. However, given that the optimal values of the multipliers of model (A11) may not be exclusive, it is probable that the decomposed overall efficiency scores may also not be unique. Kao and Hwang (2008) mitigated this bias by attributing higher seniority to one of the stages comprising the overall system (i.e., the allied stages and stage 3) and computing its efficiency score foremost, ceteris paribus. Thus, given that the allied stage has seniority over stage 3, then the efficiency of the allied stage $e_o^{1,2}$ is measured foremost whilst holding the optimal overall efficiency specified in model (2.2) constant at $e_o^{1,2,3*}$ using

$$e_o^{1,2*} = Max \frac{\sum_{t=1}^{j} b_t^{1,2} B_{t0} + \sum_{u=1}^{k} c_u^2 C_{u0}}{\sum_{s=1}^{i} a_s A_{s0} + \sum_{o=1}^{z} g_o^1 G_{o0} + \sum_{t=1}^{j} b_t^{1,2} B_{t0} + \sum_{w=1}^{m} e_w E_{w0}} \tag{2.4}$$

Constraint $\quad \sum_{t=1}^{j} b_t^{1,2} B_{t0} \leq \sum_{s=1}^{i} a_s A_{s0} + \sum_{o=1}^{z} g_o^1 G_{o0}; \quad a_s, g_o^1, b_t^{1,2} \geq 0$

$$\sum_{u=1}^{k} c_u^2 C_{u0} \leq \sum_{t=1}^{j} b_t^{1,2} B_{t0} + \sum_{w=1}^{m} e_w E_{w0}; \quad b_t^{1,2}, c_u^2, e_w \geq 0$$

$$\sum_{v=1}^{l} d_v D_{vx} + \sum_{o=1}^{z} g_o^3 G_{ox} \leq \sum_{u=1}^{k} c_u^3 C_{ux} + \sum_{y=1}^{r} f_y F_{yx}; \quad d_v, g_o^3, c_u^3\ f_y \geq 0$$

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[5] $*$ denote optimal values obtained in the corresponding model.

$$\sum_{t=1}^{j} b_t^{1,2*} B_{t0} + \sum_{u=1}^{k} c_u^{2*} C_{u0} + \sum_{v=1}^{l} d_v^{*} D_{v0} + \sum_{o=1}^{z} g_o^{3*} G_{o0} = e_o^{1,2,3*}$$

$$\left(\sum_{s=1}^{i} a_s A_{s0} + \sum_{o=1}^{z} g_o^{1} G_{o0} + \sum_{t=1}^{j} b_t^{1,2} B_{t0} + \sum_{w=1}^{m} e_w E_{w0} + \sum_{u=1}^{k} c_u^{3} C_{u0} + \sum_{y=1}^{r} f_y F_{y0}\right)$$

$$c_u^2 \geq c_u^3 \text{ and } g_o^3 \geq g_o^1; \quad u, o = 1,2,3, \dots, u_2;\ o_3$$

The allied efficiency is estimated as

$$e_o^{1,2*} = \frac{\sum_{t=1}^{j} b_t^{1,2*} B_{t0} + \sum_{u=1}^{k} c_u^{2*} C_{u0}}{\sum_{s=1}^{i} a_s^{*} A_{s0} + \sum_{o=1}^{z} g_o^{1*} G_{o0} + \sum_{t=1}^{j} b_t^{1,2*} B_{t0} + \sum_{w=1}^{m} e_w^{*} E_{w0}} \tag{2.5}$$

Stage 3 efficiency $e_o^{3_B}$ is subsequently computed using $e_o^{1,2,3*} = W_{1,2}^{*} e_o^{1,2_A*} + W_3^{*} e_o^{3_B}$ where $W_{1,2}^{*}$ and W_3^{*} are the optimal weighting of the allied stage and stage 3 respectively[6]. These are computed via substitution of the optimal multiplier values in model (2.4) into (A9) and (A10). However, due to the plausible presence of imbalance within the intermediate variables relating the allied stage to stage 3, I avoid using the above specification when computing the stage 3 efficiency. Galagedera et al. (2018) suggested that the IRI computed using the optimal multipliers from model (2.4) is not likely to be unique. Following these reasoning, I measure the stage 3 efficiency after controlling for IRI by generating a unique value for $IRI_0^{1,2/3}$. The subsequent section describes the process of computing the unique value for $IRI_0^{1,2/3}$ and the stage-level efficiencies.

Step 2: Controlling for intermediate and feedback imbalance

To compute the unique value for $IRI_0^{1,2/3}$, I maximize $\left(\sum_{u=1}^{k} c_u^2 C_{ux} - \sum_{u=1}^{k} c_u^3 C_{ux}\right)$ and $\left(\sum_{o=1}^{z} g_o^3 G_{ox} - \sum_{o=1}^{z} g_o^1 G_{ox}\right)$ while holding the overall efficiency for the three combined

---

[6] A and B superscripts accompanying $e_o^{1,2}$ and e_o^{3} gives an indication of which component in the overall model is prioritized in the overall efficiency decomposition. E.g., A in $e_o^{1,2_A*}$ implies that the allied stage has seniority over stage 3. Likewise, where stage 3 is given preference, $e_o^{3_B} = \frac{\sum_{v=1}^{l} d_v D_{vx} + \sum_{o=1}^{z} g_o^3 G_{ox}}{\sum_{u=1}^{k} c_u^3 C_{ux} + \sum_{y=1}^{r} f_y F_{yx}}$ is maximized subject to the model (2.4) constraints. Given that the efficiency of stage 3 is $e_o^{3_B*}$ and that of the allied stage is $e_o^{1,2_A*}$, then following the above reasoning, the efficiency decomposition is unique if $e_o^{3_B*} = e_o^{3_B}$ and $e_o^{1,2_A*} = e_o^{1,2}$. See Liang et al. (2008) for models examining whether or not the efficiency decomposition is unique.

stages specified in model (2.2) constant at $e_o^{1,2,3*}$ and the allied stage efficiency specified in model (2.1) at $e_o^{1,2*}$. When maximized, $\left(\sum_{u=1}^{k} c_u^2 C_{ux} - \sum_{u=1}^{k} c_u^3 C_{ux}\right)$ and $\left(\sum_{o=1}^{z} g_o^3 G_{ox} - \sum_{o=1}^{z} g_o^1 G_{ox}\right)$ may be interpreted as allowing $\left(\sum_{u=1}^{k} c_u^2 C_{ux}\right)$ and $\left(\sum_{o=1}^{z} g_o^3 G_{ox}\right)$ (i.e., the implied value of the output of the allied stage and feedback output from stage 3) to produce a greater value and $\left(\sum_{u=1}^{k} c_u^3 C_{ux}\right)$ and $\left(\sum_{o=1}^{z} g_o^1 G_{ox}\right)$ (i.e., implied value of the input of stage 3 and feedback input to stage 1) to produce a lower value. This procedure allows for some level of flexibility to the allied stage and stage 3 to facilitate self-evaluation of their performance favorably. This is also consistent with the hypothesis that allied stages (market-level) and stage 3 (firm-level) have distinct risk profiles and may operate under distinct environmental conditions.

The linear programming model solved here is

$$Max\left[\left(\sum_{u=1}^{k} \gamma_u^2 C_{ux} - \sum_{u=1}^{k} \gamma_u^3 C_{ux}\right) + \left(\sum_{o=1}^{z} \rho_o^3 G_{ox} - \sum_{o=1}^{z} \rho_o^1 G_{ox}\right)\right] \tag{2.6}$$

Constraint

$$\sum_{t=1}^{j} \theta_t^{1,2} B_{tx} \leq \sum_{s=1}^{i} \sigma_s A_{sx} + \sum_{o=1}^{z} \rho_o^1 G_{ox} \; ; \quad \sigma_s, \rho_o^1, \theta_t^{1,2} \geq 0$$

$$\sum_{u=1}^{k} \gamma_u^2 C_{ux} \leq \sum_{t=1}^{j} \theta_t^{1,2} B_{tx} + \sum_{w=1}^{m} \vartheta_w E_{wx} \; ; \quad \theta_t^{1,2}, \gamma_u^2, \vartheta_w \geq 0$$

$$\sum_{v=1}^{l} \varphi_v D_{vx} + \sum_{o=1}^{z} \rho_o^3 G_{ox} \leq \sum_{u=1}^{k} \gamma_u^3 C_{ux} + \sum_{y=1}^{r} \aleph_y F_{yx} \; ; \quad \varphi_v, \rho_o^3, \gamma_{u,}^3 \aleph_y \geq 0$$

$$\frac{\sum_{t=1}^{j} \theta_t^{1,2*} B_{t0} + \sum_{u=1}^{k} \gamma_u^{2*} C_{u0} + \sum_{v=1}^{l} \varphi_v^* D_{v0} + \sum_{o=1}^{z} \rho_o^{3*} G_{O0}}{\sum_{s=1}^{i} \sigma_s A_{s0} + \sum_{o=1}^{z} \rho_o^1 G_{O0} + \sum_{t=1}^{j} \theta_t^{1,2} B_{t0} + \sum_{w=1}^{m} \vartheta_w E_{w0} + \sum_{u=1}^{k} \gamma_u^3 C_{u0} + \sum_{y=1}^{r} \aleph_y F_{y0}} = e_o^{1,2,3*}$$

$$\gamma_u^2 \geq \gamma_u^3 \text{ and } \rho_o^3 \geq \rho_o^1; \quad u, o = 1,2,3,\ldots,u_2;\; o_3$$

$$e_o^{1,2_A*} = \frac{\sum_{t=1}^{j} \theta_t^{1,2} B_{t0} + \sum_{u=1}^{k} \gamma_u^2 C_{u0}}{\sum_{s=1}^{i} \sigma_s A_{s0} + \sum_{o=1}^{z} \rho_o^1 G_{O0} + \sum_{t=1}^{j} \theta_t^{1,2} B_{t0} + \sum_{w=1}^{m} \vartheta_w E_{w0}} \tag{2.7}$$

Following Galagedera et al. (2018), the optimal adverse level of IRI between the allied stage and stage 3 is calculated as

$$IRI_0^{1,2/3*} = \frac{\sum_{u=1}^{k} \gamma_u^{3*} C_{ux} + \sum_{o=1}^{z} \rho_o^{1*} G_{Ox}}{\sum_{u=1}^{k} \gamma_u^{2*} C_{ux} + \sum_{o=1}^{z} \rho_o^{3*} G_{Ox}}; \tag{2.8}$$

where $\gamma_u^{3*}, \gamma_u^{2*}, \rho_o^{1*}$ and ρ_o^{3*} are the optimal values of the conforming multipliers. Thus, the optimal opposing level of IRI for the overall interbank funding and risk management process as depicted in Figure 2.1 is specified as

$$IRI_0^* = IRI_0^{1-2} \times IRI_0^{1,2/3*} \tag{2.9}$$

IRI_0^* can be referred to as IRI index of DMU$_p$. By assumption $IRI_0^{1-2*} = 1$ (see model A7) and thus, $IRI_0^* = IRI_0^{1,2/3*}$. Where IRI_0^* = 1, it implies a perfect balance in the usage of the intermediate and feedback resources in the overall interbank funding and risk management process and thus considered a desired condition for DMU$_0$. Moreover, because $\gamma_u^{3*}, \gamma_u^{2*}, \rho_o^{1*}$ and $\rho_o^{3*} \geq \varepsilon$; where $\gamma_u^2 \geq \gamma_u^3$ and $\rho_o^3 \geq \rho_o^1$; for all $u, o = 1,2,3, \ldots, u_2;\ o_3$, I have that $0 < IRI_0^* \leq 1$. A reduced value of IRI_0^* implies a higher aggregate level of resource management between the allied stage and stage 3.

Step 3: Determining independent stage-level efficiency

The efficiency of each independent stage (1, 2, and 3) of DMU$_p$ is computed after determining the optimum allied stage efficiency whilst holding the optimum overall efficiency constant and under the most severe possible outcome IRI. Then the efficiency scores are computed via the optimum multiplier values produced in model (A7) and specified as:

$$e_o^1 = Max \frac{\sum_{t=1}^{j} \theta_t^{1*} B_{t0}}{\sum_{s=1}^{i} \sigma_s^* A_{s0} + \sum_{o=1}^{z} \rho_o^{1*} G_{o0}} \tag{2.10}$$

$$e_o^2 = Max \frac{\sum_{u=1}^{k} \gamma_u^{2*} C_{u0}}{\sum_{t=1}^{j} \theta_t^{2*} B_{t0} + \sum_{w=1}^{m} \vartheta_w^* E_{w0}} \tag{2.11}$$

$$e_o^3 = Max \frac{\sum_{v=1}^{l} \varphi_v^* D_{v0} + \sum_{o=1}^{z} g_o^3 G_{o0}}{\sum_{u=1}^{k} \gamma_u^{3*} C_{u0} + \sum_{y=1}^{r} \aleph_y^* F_{y0}} \tag{2.12}$$

All analyses in this chapter were carried out using the MaxDEA 7 Ultra software. The MaxDEA 7 Ultra software is one of the most powerful software for envelopment analysis as it allows for estimation of the most comprehensive DEA models and all their possible combinations. Table 1C in Appendix C reports the summary statistics of all the variables that have been used in the core DEA analysis.

2.4. Results and discussion

2.4.1. Descriptive statistics

Panel A of Table 2.2 shows the summary statistics of relative efficiency scores of all banks with operations on the interbank market. In Panel B and C, I segregate the summary statistics to show the relative efficiency scores for domestic and international banks. Panel A shows that the average overall management efficiency score of all banks is 0.374 with coefficient of variation (CV) 0.757. For the independent stages, the average (CV) efficiency score for the interbank funding stage, risk management stage, performance stage, and the allied process stage are 0.276 (1.308), 0.200 (1.635), 0.452 (0.735), and 0.607 (0.435) respectively. The overall performance of domestic and international banks also has similar characteristics. The average overall management efficiency score for domestic banks is 0.494 (CV = 0.632) and for international banks is 0.335 (CV = 0.788). In general, international banks exhibit a slightly higher degree of variability relative to domestic banks. In Panel B, the domestic banks, the average efficiency score for the interbank funding stage, risk management stage, performance stage and the allied process stage is 0.232, 0.127, 0.580 and 0.464 with their corresponding coefficient of variation of 1.349, 1.976, 0.495 and 0.407 respectively. In Panel C, the international banks, the average efficiency score for the interbank funding stage, risk management stage, performance stage and the allied process stage is 0.290, 0.224, 0.411 and 0.655 with their corresponding coefficient of variation of 1.300, 1.545, 0.820 and 0.412 respectively. Overall, both domestic and international banks have similar strengths.

Nevertheless, I perform further tests to assess whether there is any difference in performance between domestic and international banks. The study adopts the non-parametric test of equality of the median efficiency scores of the two groups which is grounded on order statistics[7] (Banker et al., 2010). From the test result reported in the last row of Table 2.2, the difference in the median efficiency scores of domestic and international banks is statistically significant at the 5% level for all stages with the

[7] The test statistic is $\hat{Z} = \left(\widehat{P_1} - \widehat{P_2}\right) / \sqrt{\hat{P}\left(1-\hat{P}\right)\left(\frac{1}{N_1} + \frac{1}{N_2}\right)}$, where $\widehat{P_1} = \frac{n_1}{N_1}$, $\widehat{P_2} = \frac{n_2}{N_2}$, $\hat{P} = \left(N_1\widehat{P_2} + N_1\widehat{P_2}\right)/(N_1 + N_2)$, N_1 and N_2 represent the sample size of group 1 and group 2 and n_1 and n_2 are the number of observations in group 1 and group 2 that are lower than the median observation in the full sample.

exception of the interbank funding stage. Hence, implying that all banks in the sample, regardless of whether its domestic or international, use some form of interbank funds. A plausible explanation for the difference in relative efficiency scores for the other stages may be attributed to exposures from international operations which may necessitate international banks to have more sophisticated risk management frameworks if they want to attain greater profits (Lehar, 2005; Aebi et al., 2012). Therefore, of the 9 banks that are overall risk efficient, 8 of them (89 percent) are international banks.

Table 2.2: Summary statistics of relative efficiency scores of domestic, Int'l and all banks

	Interbank Funding Relative Efficiency	Risk Management Relative Efficiency	Performance Relative Efficiency	Allied Process Relative Efficiency	Overall Management Relative Efficiency
Panel A: All Banks (N = 93)					
Mean	0.276	0.200	0.452	0.607	0.374
Std. Dev	0.361	0.327	0.332	0.264	0.283
Min	0.000	0.000	0.005	0.025	0.008
Median	0.073	0.037	0.365	0.622	0.326
Max	1.000	1.000	1.000	1.000	1.000
25^{th} Percentile	0.042	0.006	0.167	0.383	0.182
75^{th} Percentile	0.323	0.175	0.675	0.801	0.497
No. of Efficient Banks	11 (11.83%)	9 (9.68%)	17 (18.28%)	10 (10.75%)	8 (8.60%)
Panel B: Domestic Banks (N = 23)					
Mean	0.232	0.127	0.580	0.464	0.494
Std. Dev	0.313	0.251	0.287	0.189	0.312
Min	0.000	0.000	0.011	0.171	0.052
Median	0.072	0.007	0.543	0.420	0.380
Max	0.985	1.000	1.000	0.766	1.000
25^{th} Percentile	0.018	0.000	0.377	0.301	0.254
75^{th} Percentile	0.377	0.114	0.779	0.630	0.814
No. of Efficient Banks	0 (0.00%)	1 (4.35%)	5 (21.74%)	0 (0.00%)	3 (13.04%)
Panel C: Int'l Banks (N = 70)					
Mean	0.290	0.224	0.411	0.655	0.335
Std. Dev	0.377	0.346	0.337	0.270	0.264
Min	0.000	0.000	0.005	0.025	0.008
Median	0.074	0.050	0.298	0.669	0.268
Max	1.000	1.000	1.000	1.000	1.000
25^{th} Percentile	0.042	0.014	0.148	0.486	0.141
75^{th} Percentile	0.323	0.205	0.628	0.912	0.411
No. of Efficient Banks	11 (15.71%)	8 (11.43%)	12 (17.14%)	10 (14.29%)	5 (7.14%)
Test of the difference in the median relative efficiency scores of domestic and Int'l banks					
Z-Statistic	-0.588	-2.468	2.563	-3.003	2.401
P-value	0.556	0.014	0.010	0.003	0.016

2.4.2. Correlation – Linking the three stages

In Table 2.3, I report the association between all the stages using the rankings of banks based on their relative efficiency scores. The strongest association is observed between the financial performance and overall management efficiency scores with rank correlation coefficient at 0.666. Under the allied process components, the strongest association is observed between the risk management and allied process management efficiency scores with rank correlation coefficient at 0.447. The other counterpart of the allied process is interbank funding. Nevertheless, the correlation between the rankings of interbank funding and allied process management efficiency scores is not significant at 0.177. It is interesting to note that the correlation between the rankings, based on the stage level efficiency scores, that form the alliance process is statistically significant pairwise (the interbank funding and risk management processes). Hence, confirming the empirical justification for the allied stage that has been proposed; banks seeking funding on the interbank market experience increasing risk levels and their inability to manage these risks or differentiate themselves results to poor performance or returns.

Also, the direction of association is negative and further confirms my preliminary justification that banks are practically performance-driven institutions, and the ability of banks to attain superior performance is partly dependent on their level of risk taking (Hughes and Mester, 2010; Dubecq et al., 2016). Where market requirements trigger changes in bank risk management, it results to decreases in interbank activities and consequently bank performance. Out of the two processes that comprise the overall management process, it is the performance stage that has the strongest association with overall performance with rank correlation coefficient at 0.666. Interestingly, this outcome is revealed despite the higher priority given to the allied process over the performance stage in the overall efficiency decomposition. In Section 2.6, the study goes further to confirm the robustness of this outcome by changing the priority from the allied process to performance management process in overall efficiency decomposition.

In Table 2.4, I also report the variance inflation factors (VIFs), which are computed as 1/Tolerance, to further test for the potential for multicollinearity. This is diagnosed by running the collinearity diagnostic tests after our core regression model. The VIFs also reveal no sign of potential multicollinearity. The mean VIF of the variables in our sustainability-offshoring model is 1.51. The individual VIF of the variables in the correlation matrix is 1.17, 1.38, 1.80, 1.57 and 1.61 respectively. Generally, the VIF is considered high if the value is above 10 (Wooldridge, 2016). The lowest VIF for the variables in the correlation matrix is 1.17, and the highest VIF is 1.80. This suggests that multicollinearity problems are absent in the regression models. Furthermore, the Condition Number Test (k) is also used to also check for multicollinearity. The test result (k = 2.3225) is found to be far less than the threshold value of 15 (Lartey et al., 2020; Ciftci et al., 2019), and thus indicating that there are no multicollinearity issues. Generally, the findings from tables 2.3 and 2.4 show that none of the variables suffer from any serious bias that has the likelihood to affecting the reliability of the regression results.

Table 2.3: Spearman rank correlation matrix of relative efficiency scores

	Interbank Funding	Risk Management	Financial Performance	Allied Process Management	Overall Management
Interbank Funding	1.000				
Risk Management	-0.294*	1.000			
Financial Performance	0.050	-0.360*	1.000		
Allied Process Management	0.177	0.447*	-0.344*	1.000	
Overall Management	0.070*	-0.139*	0.666*	-0.363*	1.000

* Indicates statistical significance at 1% level.

Table 2.4: Collinearity diagnostics (VIF)

Variable	VIF	SQRT VIF	Tolerance	R-Squared	Eigenval	Cond Index
Interbank Funding	1.17	1.08	0.8582	0.1418	1.8917	1.0000
Risk Management	1.38	1.17	0.7245	0.2755	1.3262	1.1943
Financial Performance	1.80	1.34	0.5550	0.4450	1.0165	1.3642
Allied Process Management	1.57	1.25	0.6380	0.3620	0.4148	2.1354
Overall Management	1.61	1.27	0.6198	0.3802	0.3507	2.3225
Mean VIF	1.51		Condition Number		2.3225	

The table reports the variance inflation factors (VIF) for the relative efficiency scores.

2.4.3. Overview of overall, allied process and stage level performance

2.4.3.1. Overall bank performance

In this section, I examine the overall process performance of banks. Table 2.4 reports the top 25 overall best performing banks who are able to efficiently manage the three key processes: funding, risk and performance. Out of the ninety-three (93) banks examined, eight (8) banks comprising of three (3) domestic and five (5) international banks are efficient overall. Though earlier evidences that adopt the augmented structure of network representation of production processes contend that increased structure may add discriminatory power (Galagedera et al., 2016; Galagedera et al., 2018), this is not the case here. Of the 8 banks that are overall efficient, two (2) are efficient under the allied stage and financial performance stage. Hence, this supports the prediction in Hypothesis 2.1 that a bank should be efficient if it is able to effectively manage its interbank exposure through effective risk management. Effective management of this risk exposure should effectively increase bank performance. Out of the top fifteen (15) overall performers, seven (7) are ranked very poorly in allied process management and ten (10) are highly efficient under financial performance management. Hence, supporting the prediction that banks are performance driven and may forgo risk management in favour of higher financial performance. Trading banks can act differently given their business models, objectives and regulatory constraints. The remaining 10 banks in the bottom of the top 25 in Table 2.4 show an even balance between performance management and allied stage management. Only one bank is overly efficient under the allied stage but performed averagely under the financial performance stage. Hence, confirming that banks must manage their interbank activities and exposures effectively to enhance overall bank performance.

Table 2.5: Overall Management: Top 25 performers

	Interbank Funding		Risk Management		Performance Management		Allied Process Management		Overall Management		Intermediate Resource Imbalance	
Bank Name	RES	Rank	RES	Rank	RES	Rank	RES	Rank	RES	Rank	IRI_0^*	Rank
Goldman Sachs Int’l	1	6	0.000	90	1	9	1	6	1	5	1	1
Bank Sepah Int’l Plc	0.883	15	1	5	1	9	1	6	1	5	0.001	71
Close Brothers Ltd	0.933	13	0.029	52	0.632	26	0.734	31	1	5	0.000	83
N M Rothschild & Sons Ltd	0.000	92	1	5	1	9	0.596	49	1	5	0.001	65
Lloyds Bank Plc	0.377	22	0.000	90	1	9	0.220	86	1	5	0.063	18
Alpha Bank London Ltd	0.002	90	0.054	43	1	9	0.209	88	1	5	0.001	62
Natwest Markets Plc	0.177	35	0.000	90	1	9	0.171	91	1	5	0.221	12
Commerzbank Finance Ltd	1	6	0.005	71	1	9	0.025	93	1	5	0.000	81
Bank of Scotland Plc	0.052	60	0.000	90	1	9	0.248	83	0.968	9	0.458	6
BMO Capital Markets Ltd	0.928	14	0.943	10	0.273	56	0.920	17	0.938	10	0.001	54
National Westminster Bank Plc	0.018	78	0.000	86	1	9	0.358	73	0.916	11	0.458	6
Close Brothers Group Plc	0.437	21	0.058	42	0.582	28	0.700	36	0.814	12	0.001	67
CIBC World Markets Plc	1	6	1	5	0.009	90	1	6	0.723	13	0.002	50
Shawbrook Bank Ltd	0.591	20	0.025	54	0.556	31	0.484	65	0.685	14	0.000	87
Ahli United Bank (UK) Plc	0.001	91	0.028	53	1	9	0.260	79	0.648	15	0.002	51
JP Morgan Europe Ltd	0.032	75	0.106	30	0.360	48	0.996	12	0.641	16	0.058	20
Bank of China (UK) Ltd	0.054	59	0.087	35	0.520	35	0.509	60	0.637	17	0.001	78
The Access Bank UK Ltd	0.042	69	0.074	39	0.628	27	0.746	29	0.603	18	0.004	43
Gulf Int’l Bank (UK) Ltd	0.013	81	0.103	31	0.132	80	0.990	13	0.574	19	0.018	26
Santander UK Plc	0.107	41	0.000	90	0.557	30	0.250	82	0.562	20	0.117	15
Secure Trust Bank Plc	0.080	44	0.114	29	0.443	41	0.633	43	0.508	21	0.000	87
China Construction Bank (London)	0.042	70	0.032	51	0.740	22	0.217	87	0.507	22	0.002	52
Isle of Man Bank Ltd	0.002	89	0.083	38	0.537	34	0.622	47	0.504	23	0.005	37
Canada Square Operations Ltd	0.013	80	1	5	0.473	40	1	6	0.497	24	0.001	58
HSBC Bank Plc	0.047	64	0.000	90	0.675	24	0.414	69	0.485	25	0.350	8
Average	0.313	49.6	0.230	48.9	0.685	28.1	0.572	50.2	0.768	13.0	0.111	45.3

Notes: RES=relative efficiency score. When ranking banks (n=93) based on performance, banks are sorted based on their relative efficiency scores (RES) in descending order and assign rank 1 to the bank with the highest relative efficiency score, and rank 93 to the bank with the lowest relative efficiency score. Banks with the same relative efficiency score are assigned their average rank.

2.4.3.2. Allied process management

This section examines bank performance under the allied process. Table 2.5 reports the efficiency scores of the top 25 performers in allied process management. In this case, ten (10) banks out of the ninety-three (93) banks are efficient. Four (4) of these banks use greater interbank funding and five (5) are efficient in risk management. One bank uses greater interbank funding and is still overly efficient in risk management. Further, seven of the twenty-five banks listed in Table 2.4 are also listed in Table 2.5 suggesting the negative and significant association between the allied process and overall management performance, especially at the lower end. I observe that performance of the banks listed in Table 2.5 is generally poor. Within the top 15 of the best 25 performers in the allied process, only 3 banks are overly efficient at the financial performance stage. This is not surprising given that I prioritised the allied process stage rather than the financial performance stage in overall efficiency decomposition. Nevertheless, when I do the opposite, I observe a similar result; there is no positive association between financial performance and the allied process. I advance the lack of positive association between allied process management and financial performance observed as empirical justification (value added) for conceptualising that the overall bank performance management process is a production process that comprises multiple stages.

In fact, I observe that high financial or overall performance may not necessarily suggest high allied process performance. The top ranked financial performers actually are the worse ranked performers under the allied process. Hence, the empirical evidence suggests that while good overall management performance may suggest better management of exposure from interbank activities (allied process), better allied process performance may not signal good overall management performance. It also confirms my earlier position that banks are virtually performance driven institutions whose performance objectives are independently optimal but aggregately suboptimal. Trading banks can act differently given their business models, objectives and regulatory constraints.

Table 2.6: Allied Process Management: Top 25 performers

	Interbank Funding		Risk Management		Performance Management		Allied Process Management		Overall Management		Intermediate Resource Imbalance	
Bank Name	RES	Rank	RES	Rank	RES	Rank	RES	Rank	RES	Rank	IRI_0^*	Rank
Canada Square Operations Ltd	0.013	80	1	5	0.473	40	1	6	0.497	24	0.001	58
Persia Int'l Bank Plc	0.061	55	1	5	0.250	58	1	6	0.356	40	0.001	71
Bank of Ceylon (UK) Ltd	0.073	47	1	5	0.009	89	1	6	0.007	93	0.000	81
Bank Sepah Int'l Plc	0.883	15	1	5	1	9	1	6	1	5	0.001	71
CIBC World Markets Plc	1	6	1	5	0.009	90	1	6	0.723	13	0.002	50
Havin Bank Ltd	0.141	39	0.836	12	0.005	92	1	6	0.214	59	0.001	65
British Arab Commercial Bank Plc	0.058	58	0.646	13	0.163	73	1	6	0.189	68	0.007	36
Daiwa Capital Markets Europe Ltd	1	6	0.069	41	0.315	53	1	6	0.193	65	0.050	21
Citigroup Global Markets Ltd	1	6	0.005	72	0.670	25	1	6	0.199	62	0.583	3
Goldman Sachs Int'l	1	6	0.000	90	1	9	1	6	1	5	1	1
Bank Saderat Plc	0.030	76	1	5	0.336	50	0.997	11	0.346	41	0.001	62
JP Morgan Europe Ltd	0.032	75	0.106	30	0.360	48	0.996	12	0.641	16	0.058	20
Gulf Int'l Bank (UK) Ltd	0.013	81	0.103	31	0.132	80	0.990	13	0.574	19	0.018	26
Diamond Bank (UK) Plc	0.368	23	0.863	11	0.005	93	0.958	14	0.117	78	0.001	78
Goldman Sachs Int'l Bank	1	6	0.004	75	1	9	0.952	15	0.207	60	0.192	13
Melli Bank Plc	0.063	51	0.498	16	0.230	63	0.931	16	0.180	71	0.001	67
BMO Capital Markets Ltd	0.928	14	0.943	10	0.273	56	0.920	17	0.938	10	0.001	54
Bank Of New York Mellon (Int'l) Ltd	0.825	19	0.018	60	0.248	60	0.912	18	0.278	50	0.012	27
DB UK Bank Ltd	0.013	82	0.100	32	0.081	84	0.880	19	0.028	90	0.009	32
Ghana Int'l Bank Plc	0.035	74	0.175	24	0.129	81	0.872	20	0.433	27	0.003	46
Zenith Bank (UK) Ltd	0.218	30	0.084	36	0.336	51	0.856	21	0.331	46	0.001	74
Mizuho Int'l Plc	0.834	18	0.009	65	0.166	71	0.855	22	0.241	58	0.046	22
Morgan Stanley & Co. Int'l Plc	1	6	0.007	69	0.386	44	0.833	23	0.375	34	0.371	7
TD Bank Europe Ltd	1	6	0.036	47	0.101	83	0.801	24	0.059	85	0.000	87
Credit Suisse Int'l	0.264	27	0.017	61	0.381	45	0.794	25	0.141	74	0.242	11
Average	0.474	36.2	0.421	33.0	0.322	58.2	0.942	13.0	0.371	47.7	0.104	43.1

Notes: RES=relative efficiency score. When ranking banks (n=93) based on performance, banks are sorted based on their relative efficiency scores (RES) in descending order and assign rank 1 to the bank with the highest relative efficiency score, and rank 93 to the bank with the lowest relative efficiency score. Banks with the same relative efficiency score are assigned their average rank.

2.4.3.3. Individual stage-level performance

The results so far suggest that, generally, efficient overall bank management is driven by a complement of good alliance between risk and funding, and performance. Nevertheless, the study also shows that some banks prefer superior performance outcomes at the expense of risk management. In such a case, these banks can record high financial performance ranking but lower ranking on the allied process. Hence, the need to examine any linkages between the individual stage-level outcomes and the overall process of bank performance management.

2.4.3.3.1. Interbank funding stage

I begin by examining interbank funding stage where I again limit the discussion to the 25 best performing banks. I expect that when a bank is overly reliant on interbank funding/borrowing, such bank should be highly ranked in Table 2.6. I find that eleven (11) of the ninety-three (93) banks are funding efficient implying that they use higher interbank funding. All these 11 efficient banks are international banks. Moreover, 12 out of the top 25 funding efficient performers are also amongst the top 25 allied process performers. This observation and the rank correlation between the interbank funding and the allied process efficiency scores at 0.177 (see Table 2.3) suggest that the association between them is positive. This is important information to bank managers to help them develop controls that can significantly mitigate any exposures from their interbank market activities. Although the interbank market connects financial institutions with surplus liquidity to those facing the danger of insolvency or illiquidity to temporarily cover this shortfall, both parties are exposed to a variety of exposures. Focusing solely on the financial benefits of these activities may have significant consequences for the individual banks as well as for the banking system as a whole. Given the earlier finding that there is a strong association between the allied process and overall performance management, particularly at the lower end, a key step towards achieving excellence in overall bank performance is to manage the banks' interbank funding process efficiently.

Table 2.7: Interbank Funding: Top 25 performers

	Interbank Funding		Risk Management		Performance Management		Allied Process Management		Overall Management		Intermediate Resource Imbalance	
Bank Name	RES	Rank	RES	Rank	RES	Rank	RES	Rank	RES	Rank	IRI_0^*	Rank
CIBC World Markets Plc	1	6	1	5	0.009	90	1	6	0.723	13	0.002	50
Citigroup Global Markets Ltd.	1	6	0.005	72	0.670	25	1	6	0.199	62	0.583	3
Commerzbank Finance Ltd.	1	6	0.005	71	1	9	0.025	93	1	5	0.000	81
Daiwa Capital Markets Europe Ltd	1	6	0.069	41	0.315	53	1	6	0.193	65	0.050	21
Goldman Sachs Int’l	1	6	0.000	90	1	9	1	6	1	5	1	1
Goldman Sachs Int’l Bank	1	6	0.004	75	1	9	0.952	15	0.207	60	0.192	13
Jefferies Int’l Ltd	1	6	0.092	33	0.474	39	0.659	41	0.332	44	0.011	28
Merrill Lynch Int’l	1	6	0.000	84	0.439	42	0.507	61	0.182	70	0.500	4
Morgan Stanley & Co. Int’l Plc	1	6	0.007	69	0.386	44	0.833	23	0.375	34	0.371	7
TD Bank Europe Ltd	1	6	0.036	47	0.101	83	0.801	24	0.059	85	0.000	87
UBS Ltd.	1	6	0.004	76	0.225	64	0.674	39	0.258	53	0.087	17
Sainsbury's Bank Plc	0.984	12	0.235	22	0.494	37	0.547	55	0.143	73	0.000	87
Close Brothers Ltd.	0.933	13	0.029	52	0.632	26	0.734	31	1	5	0.000	83
BMO Capital Markets Ltd.	0.928	14	0.943	10	0.273	56	0.920	17	0.938	10	0.001	54
Bank Sepah Int’l Plc	0.883	15	1.000	5	1	9	1	6	1	5	0.001	71
Nomura Int’l Plc	0.882	16	0.003	77	0.571	29	0.542	56	0.192	67	0.338	9
Metro Bank Plc	0.844	17	0.004	74	0.011	88	0.301	78	0.052	88	0.001	74
Mizuho Int’l Plc	0.834	18	0.009	65	0.166	71	0.855	22	0.241	58	0.046	22
Bank Of New York Mellon (Int’l)	0.825	19	0.018	60	0.248	60	0.912	18	0.278	50	0.012	27
Shawbrook Bank Ltd.	0.591	20	0.025	54	0.556	31	0.484	65	0.685	14	0.000	87
Close Brothers Group Plc	0.437	21	0.058	42	0.582	28	0.700	36	0.814	12	0.001	67
Lloyds Bank Plc	0.377	22	0.000	90	1	9	0.220	86	1	5	0.063	18
Diamond Bank (UK) Plc	0.368	23	0.863	11	0.005	93	0.958	14	0.117	78	0.001	78
ITAU BBA Int’l Plc	0.323	24	0.014	63	0.238	62	0.536	58	0.368	36	0.001	60
Morgan Stanley Bank Int’l Ltd.	0.309	25	0.009	64	1	9	0.360	72	0.397	32	0.007	36
Average	0.821	13.0	0.177	54.1	0.496	43.0	0.701	37.3	0.470	41.0	0.131	43.2

Notes: RES=relative efficiency score. When ranking banks (n=93) based on performance, banks are sorted based on their relative efficiency scores (RES) in descending order and assign rank 1 to the bank with the highest relative efficiency score, and rank 93 to the bank with the lowest relative efficiency score. Banks with the same relative efficiency score are assigned their average rank.

2.4.3.3.2. Risk management

In this section, I examine bank risk management performance. In today's more complex, interrelated global business environment, risk management has been the foundation of several key policies regulating performance of financial institutions such as commercial banks (Pagano, 2001; Ratnovski, 2013). Inherently, banks must manage several risks in the course of production and delivery of various financial services in order to create value for its shareholders and customers. I expect that a bank that has highly sophisticated risk management processes should achieve a higher ranking on risk management. I find that nine (9) banks of the ninety-three (93) are risk management efficient. On average, bank performance (stage 3) is generally poor with only two of the 9 banks ranked efficient financial performers. Among the top 25 risk efficient banks, only four are in the top 25 ranked banks under financial performance (stage 3). This is consistent with the rank correlation coefficients reported in Table 2.7, there is a significant but negative association risk management and banks performance.

This is further supported by the negative association between risk management and overall bank performance. Hence, confirming that because banks are performance driven institutions, highly sophisticated risk management processes decrease their performance. Further, 10 out of the top 15 efficient risk management banks are also amongst the top 15 allied process performers. This supports the rank correlation of a positive and significant association between risk management and the allied process. The interbank market exposes banks to extreme risks which must be effectively managed to attain better performance. Bank managers sometimes take these processes lightly in their pursuit for higher bank performance. In fact, Saunders (1997) and Saunders et al., (2006) contend that modern financial institutions are actively involved in the business of risk-management to the extent of selling their services as risk specialists. Evidence also suggests that the presence of a chief risk officer (CRO) on bank's executive board: the line of reporting of the CRO, and other risk management-related corporate governance mechanisms (i.e., risk governance) affect bank performance (Aebi et al., 2012).

Table 2.8: Risk Management: Top 25 performers

Bank Name	Interbank Funding RES	Interbank Funding Rank	Risk Management RES	Risk Management Rank	Performance Management RES	Performance Management Rank	Allied Process Management RES	Allied Process Management Rank	Overall Management RES	Overall Management Rank	Intermediate Resource Imbalance IRI_0^*	Intermediate Resource Imbalance Rank
C. Hoare & Co	0.000	93	1	5	0.248	59	0.372	71	0.363	37	0.002	49
N M Rothschild & Sons Ltd	0.000	92	1	5	1	9	0.596	49	1	5	0.001	65
Canada Square Operations Ltd	0.013	80	1	5	0.473	40	1	6	0.497	24	0.001	58
Bank Saderat Plc	0.030	76	1	5	0.336	50	0.997	11	0.346	41	0.001	62
Turkish Bank (UK) Ltd	0.035	73	1	5	0.015	87	0.722	34	0.015	92	0.000	92
Persia Int’l Bank Plc	0.061	55	1	5	0.250	58	1	6	0.356	40	0.001	71
Bank of Ceylon (UK) Ltd	0.073	47	1	5	0.009	89	1	6	0.007	93	0.000	81
Bank Sepah Int’l Plc	0.883	15	1	5	1	9	1	6	1	5	0.001	71
CIBC World Markets Plc	1	6	1	5	0.009	90	1	6	0.723	13	0.002	50
BMO Capital Markets Ltd	0.928	14	0.943	10	0.273	56	0.920	17	0.938	10	0.001	54
Diamond Bank (UK) Plc	0.368	23	0.863	11	0.005	93	0.958	14	0.117	78	0.001	78
Havin Bank Ltd	0.141	39	0.836	12	0.005	92	1	6	0.214	59	0.001	65
British Arab Commercial Bank Plc	0.058	58	0.646	13	0.163	73	1	6	0.189	68	0.007	36
Julian Hodge Bank Ltd	0.016	79	0.623	14	0.543	33	0.629	44	0.374	35	0.000	92
Sonali Bank (UK) Ltd	0.035	72	0.546	15	0.021	86	0.593	50	0.027	91	0.001	71
Melli Bank Plc	0.063	51	0.498	16	0.230	63	0.931	16	0.180	71	0.001	67
United National Bank Ltd	0.208	31	0.465	17	0.510	36	0.766	26	0.083	84	0.000	92
Union Bank UK Plc	0.048	62	0.328	18	0.167	69	0.761	27	0.141	75	0.001	54
Bank Mandiri (Europe) Ltd	0.152	38	0.308	19	0.134	79	0.456	67	0.110	80	0.000	90
Wesleyan Bank Ltd	0.006	86	0.261	20	0.418	43	0.253	81	0.398	31	0.000	83
Punjab National Bank (Int’l) Ltd	0.008	83	0.240	21	0.243	61	0.624	45	0.199	63	0.001	54
Sainsbury's Bank Plc	0.984	12	0.235	22	0.494	37	0.547	55	0.143	73	0.000	87
BMCE Bank Int’l Plc	0.061	54	0.205	23	0.916	18	0.677	38	0.404	29	0.001	71
Ghana Int’l Bank Plc	0.035	74	0.175	24	0.129	81	0.872	20	0.433	27	0.003	46
Habib Allied Holding Ltd	0.007	85	0.145	26	0.843	19	0.486	63	0.108	81	0.001	58
Habibsons Bank Ltd	0.007	85	0.145	26	0.063	85	0.486	64	0.058	86	0.001	58
Average	0.201	57.0	0.633	13.5	0.327	58.3	0.756	31.9	0.324	53.5	0.001	67.2

Notes: RES=relative efficiency score. When ranking banks (n=93) based on performance, banks are sorted based on their relative efficiency scores (RES) in descending order and assign rank 1 to the bank with the highest relative efficiency score, and rank 93 to the bank with the lowest relative efficiency score. Banks with the same relative efficiency score are assigned their average rank.

2.4.3.3.3. Stage-level financial performance

In Table 2.8, I report the top 25 financially efficient banks. The results show that seventeen (17) of the ninety-three (93) banks are financially efficient. Half the banks listed in Table 2.8 are also listed in Table 2.4 suggesting that financial performance and overall management performance may have a strong positive association in the case of high-end financial performers. This outcome is achieved in spite of giving priority to the allied process. The empirical evidence suggests that bank managers rely more on financial performance as a benchmark to gauge their overall management performance at the expense of sophisticated risk management. Further, I find that on average, the top financially performing banks are ranked poorly in other aspects such as risk management. This outcome is achieved even though evidence suggests that sound risk management practices have been the backbone of commercial banking in recent years.

Table 2.9: Performance Management: Top 25 performers

	Interbank Funding		Risk Management		Performance Management		Allied Process Management		Overall Management		Intermediate Resource Imbalance	
Bank Name	RES	Rank	RES	Rank	RES	Rank	RES	Rank	RES	Rank	IRI_0^*	Rank
Commerzbank Finance Ltd	1	6	0.005	71	1	9	0.025	93	1	5	0.000	81
Sg Kleinwort Hambros Bank Ltd	0.065	50	0.008	66	1	9	0.104	92	0.129	77	0.000	87
Natwest Markets Plc	0.177	35	0.000	90	1	9	0.171	91	1	5	0.221	12
TSB Bank Plc	0.175	36	0.001	83	1	9	0.208	89	0.278	51	0.007	34
Alpha Bank London Ltd	0.002	90	0.054	43	1	9	0.209	88	1	5	0.001	62
Lloyds Bank Plc	0.377	22	0.000	90	1	9	0.220	86	1	5	0.063	18
Bank of Scotland Plc	0.052	60	0.000	90	1	9	0.248	83	0.968	9	0.458	6
Ahli United Bank (UK) Plc	0.001	91	0.028	53	1	9	0.260	79	0.648	15	0.002	51
National Westminster Bank Plc	0.018	78	0.000	86	1	9	0.358	73	0.916	11	0.458	6
Morgan Stanley Bank Int'l Ltd	0.309	25	0.009	64	1	9	0.360	72	0.397	32	0.007	36
Bank of Beirut (UK) Ltd	0.044	67	0.122	28	1	9	0.553	54	0.483	26	0.001	62
National Bank of Egypt (UK) Ltd	0.047	65	0.072	40	1	9	0.554	53	0.410	28	0.004	42
N M Rothschild & Sons Ltd	0.000	92	1	5	1	9	0.596	49	1	5	0.001	65
Royal Bank of Scotland Int'l Ltd	0.005	87	0.004	73	1	9	0.724	33	0.380	33	0.121	14
Goldman Sachs Int'l Bank	1	6	0.004	75	1	9	0.952	15	0.207	60	0.192	13
Bank Sepah Int'l Plc	0.883	15	1	5	1	9	1	6	1	5	0.001	71
Goldman Sachs Int'l	1	6	0.000	90	1	9	1	6	1	5	1	1
BMCE Bank Int'l Plc	0.061	54	0.205	23	0.916	18	0.677	38	0.404	29	0.001	71
Habib Allied Holding Ltd	0.007	85	0.145	26	0.843	19	0.486	63	0.108	81	0.001	58
Barclays Bank Plc	0.058	57	0.000	90	0.779	20	0.420	68	0.203	61	0.833	2
FBN Bank (UK) Ltd	0.045	66	0.020	58	0.751	21	0.357	74	0.057	87	0.005	39
China Construction Bank (London)	0.042	70	0.032	51	0.740	22	0.217	87	0.507	22	0.002	52
Standard Chartered Bank	0.044	68	0.000	86	0.738	23	0.352	75	0.345	42	0.329	10
HSBC Bank Plc	0.047	64	0.000	90	0.675	24	0.414	69	0.485	25	0.350	8
Citigroup Global Markets Ltd	1	6	0.005	72	0.670	25	1	6	0.199	62	0.583	3
Average	0.258	52.0	0.109	61.9	0.924	13.0	0.459	61.6	0.565	31.3	0.186	36.0

Notes: RES=relative efficiency score. When ranking banks (n=93) based on performance, banks are sorted based on their relative efficiency scores (RES) in descending order and assign rank 1 to the bank with the highest relative efficiency score, and rank 93 to the bank with the lowest relative efficiency score. Banks with the same relative efficiency score are assigned their average rank.

2.3.4.4. Intermediate resource imbalance

The measure of intermediate resource imbalance, IRI_0^*, ranges between 0 and 1 (inclusive) where IRI_0^* = 1 reveals no IRI. Therefore, IRI_0^* = 1 is interpreted as the most efficient use of internal resources. The results suggest that IRI_0^* based bank rankings are associated with the rankings based on the performance on all the three aspects of bank performance management modelled in the analysis. Hence, I use the IRI_0^* as an index aimed towards providing further information on managerial performance.

Table 2.9 lists the banks rankings on IRI_0^*. There is only one bank (Goldman Sachs International) that recorded $IRI_0^* = 1$ among the 93 banks analysed. This bank is efficient in all the aspects of bank performance management. Hence, overall, Goldman Sachs International can be recognised as the most efficiently performing bank among the 93 banks analysed. This bank is able to effectively manage its internal resources, risk exposure and performance concurrently. Among the top 25 banks ranked on IRI_0^*, only two banks namely, National Westminster Bank Plc and Lloyds Bank Plc are ranked efficient while five others belong to the top-25 category under overall bank management performance. As suggested by Galagedera et al., (2018), the IRI_0^* is utilised to practically discriminate between banks ranked equal at any level of performance. For instance, Table 2.4 reveals that eight (8) banks are efficient under overall management but only two banks are allied process management efficient. These two alliance efficient banks have the same efficiency score of one and hence the same rank. Nevertheless, their IRI_0^* values differ. I rank the efficient bank with the highest IRI_0^*, Goldman Sachs International with IRI_0^* = 1.00 above the other bank which is Bank Sepah International Plc because higher the IRI_0^* implies better efficiency in the utilisation of internal resources[8].

[8] It is probable that two or more banks may record equal RES ranking whether efficient or not and also have the same IRI_0^*. Under such scenario, it is not possible to discriminate between banks based on the IRI_0^* solely. Performance in the other independent aspects may complement the IRI_0^* discriminating process. For instance, Table 2.9 reveals that Bank of Scotland Plc and National Westminster Bank Plc are financial performance efficient (RES = 1) and both of these banks have the same $IRI_0^* = 6$.

Table 2.10: Intermediate resource imbalance: Top 25 performers

	Interbank Fund Management		Risk Management		Performance Management		Allied Process Management		Overall Management		Intermediate Resource Imbalance	
Bank Name	RES	Rank	RES	Rank	RES	Rank	RES	Rank	RES	Rank	IRI_0^*	Rank
Goldman Sachs Int'l	1	6	0.000	90	1	9	1	6	1	5	1	1
Barclays Bank Plc	0.058	57	0.000	90	0.779	20	0.420	68	0.203	61	0.833	2
Citigroup Global Markets Ltd.	1	6	0.005	72	0.670	25	1	6	0.199	62	0.583	3
Merrill Lynch Int'l	1	6	0.000	84	0.439	42	0.507	61	0.182	70	0.500	4
National Westminster Bank Plc	0.018	78	0.000	86	1	9	0.358	73	0.916	11	0.458	6
Bank of Scotland Plc	0.052	60	0.000	90	1	9	0.248	83	0.968	9	0.458	6
Morgan Stanley & Co. Int'l Plc	1	6	0.007	69	0.386	44	0.833	23	0.375	34	0.371	7
HSBC Bank Plc	0.047	64	0.000	90	0.675	24	0.414	69	0.485	25	0.350	8
Nomura Int'l Plc	0.882	16	0.003	77	0.571	29	0.542	56	0.192	67	0.338	9
Standard Chartered Bank	0.044	68	0.000	86	0.738	23	0.352	75	0.345	42	0.329	10
Credit Suisse Int'l	0.264	27	0.017	61	0.381	45	0.794	25	0.141	74	0.242	11
Natwest Markets Plc	0.177	35	0.000	90	1	9	0.171	91	1	5	0.221	12
Goldman Sachs Int'l Bank	1	6	0.004	75	1	9	0.952	15	0.207	60	0.192	13
Royal Bank of Scotland Int'l Ltd.	0.005	87	0.004	73	1	9	0.724	33	0.380	33	0.121	14
Santander Uk Plc	0.107	41	0.000	90	0.557	30	0.250	82	0.562	20	0.117	15
RBC Europe Ltd.	0.081	43	0.002	79	0.150	74	0.751	28	0.401	30	0.112	16
UBS Ltd.	1	6	0.004	76	0.225	64	0.674	39	0.258	53	0.087	17
Lloyds Bank Plc	0.377	22	0.000	90	1	9	0.220	86	1	5	0.063	18
JP Morgan Europe Ltd.	0.032	75	0.106	30	0.360	48	0.996	12	0.641	16	0.058	20
Scotiabank Europe Plc	0.188	33	0.018	59	0.143	76	0.717	35	0.250	56	0.058	20
Daiwa Capital Markets Europe Ltd.	1.000	6	0.069	41	0.315	53	1	6	0.193	65	0.050	21
Mizuho Int'l Plc	0.834	18	0.009	65	0.166	71	0.855	22	0.241	58	0.046	22
ICBC Standard Bank Plc	0.266	26	0.006	70	0.142	77	0.651	42	0.177	72	0.029	23
Royal Bank of Canada (Channel Islands)	0.004	88	0.022	56	0.483	38	0.692	37	0.359	39	0.027	24
Sumitomo Mitsui Banking Corp Europe	0.180	34	0.002	81	0.123	82	0.664	40	0.292	48	0.018	25
Average	0.425	36.6	0.011	74.8	0.572	37.1	0.631	44.5	0.439	40.7	0.266	13.0

Notes: RES=relative efficiency score. When ranking banks (n=93) based on performance, banks are sorted based on their relative efficiency scores (RES) in descending order and assign rank 1 to the bank with the highest relative efficiency score, and rank 93 to the bank with the lowest relative efficiency score. Banks with the same relative efficiency score are assigned their average rank.

2.5. Robustness checks

2.5.1. Change in priority in overall efficiency decomposition

In decomposing the overall efficiency scores in equation (2.11), I prioritised the allied process over financial performance. Hence, all the results discussed so far are interpreted under this assumption. To validate and enhance the robustness of my findings, I compare the results when the financial performance stage is given priority over the allied process and vice versa. Figure 2.2 reports the graphical representation of the rankings of banks based on their stage level and overall management performance produced by the two alternative priority schemes.

In Panel (a) of Figure 2.2, the results indicate that the change in priority has no significant impact on the rankings of banks that perform relatively well on interbank funding. Rather, it is the banks that performed relatively poor or are in the middle band that are affected slightly by the priority change. I observe that the rankings based on interbank funding of 46 (49.5%) banks improved when priority is changed from the allied process to financial performance. In some of these 46 banks the improvement is sizeable. The ranking of approximately 20% (9 banks) improves by at least 20 steps. According to Panel (b), the bank's ranking based on risk management is significantly affected upon the priority change. Hence, emphasizing the inverse association between performance goals and risk management. The ranking based on risk management of 45 (48.4%) banks improved when priority is changed from the allied process to financial performance. Some of these 45 banks realized substantial improvements. The ranking of approximately 38% (17 banks) improved by at least 20 steps. Again, Panel (c) confirms that a change in priority does affect bank financial performance ranking. I observe an improvement in bank ranking on financial performance of 37 (39.8%) when priority is changed. 10 (27%) of these 37 banks realized substantial improvements of at least 20 steps.

Nevertheless, Panel (d) of Figure 2.2 shows that changing the priority does not affect overall management performance-based rankings. Of the 93 banks examined, only 7 recorded slight improvements in ranking. None of the 7 banks realized an improvement beyond 1 step. Also, when the allied process is prioritised in the overall efficiency decomposition, the number of funds with IRI_0^* = 1 is 1 but when financial performance is prioritised, the number increases to 7. Without indicating a loss of discriminatory power of IRI_0^*, this further confirms and justifies my earlier position that the IRI_0^* can be used as an index that aims at providing a robust examination of managerial performance and for purposes of practically discriminating between banks ranked equal at any level of performance. With more banks recording an IRI_0^* = 1 when priority is given to financial performance, it also confirms my justification that banks are performance driven. Nevertheless, given that the rankings based on overall management efficiency scores are not affected much by change in priority (see Panel d) and the high correlation between financial performance and overall management process, prioritising the allied process over the financial performance efficiency in the overall efficiency decomposition is the better option.

Figure 2.2. Rankings based on stage-wide performance assessed under the two priority schemes in overall efficiency decomposition.

2.6. Conclusions

Extant banking literature suggest that endogenous individual bank performance objectives are imperative to understanding the evolution and malfunctioning of interbank markets (Lucchetta 2015; Liu et al., 2017). A key input to the debate emerged from Hughes and Mester (1998, 2013) who suggest the prerequisite to incorporate bank efficiency into the assessment of bank capital and risk levels. Thus, necessitating the need to advance more robust models that incorporate the multi-dimensional nature of bank operations and particularly performance. This chapter proposes a novel network DEA model to evaluate bank performance in a multi-dimensional context that incorporates exposure from the interbank market. The study conceptualises overall bank performance management as a serially linked three-stage process encompassing interbank funding, risk management and financial performance. The model highlights a feedback and alliance component where the alliance structure explains the endogenous interaction between interbank funding and bank risk. In formulating the DEA model to examine overall and stage-level efficiency scores, I condition that the unsecured interbank markets expose banks to various risks and thus, triggering changes in bank risk management. The study also models the differences in the level of risk exposure of stage-level processes through conditions imposed on the multipliers associated with intermediate measures. In so doing, I employ the novel internal resource imbalance index to assess and enhance the discriminatory power of performance. Through this performance appraisal technique, bank performance is evaluated (i) from three distinct aspects of bank objectives, and (ii) in a model with feedback, alliance and implied use of intermediate resources.

The performance evaluation approach is valuable to bank management since the findings are based on models that incorporate multiple performance objectives, and account for the extensive network representation of the overall bank performance management process. Realigning financial and bank performance to incorporate these key aspects ensures that efficiency levels recognize key segments of managerial and strategic decisions. The proposed envelopment models may have applications beyond interbank or bank efficiency assessment. Future research should consider adopting these models for the appraisal of outsourced key bank segments. It is standard practice for banks to outsource a range of their business activities either domestically and/or cross-border.

Though outsourcing creates benefits (such as cost savings, accessibility to sophisticated talent pool, better or improved funding terms, among others), common risks include contagion via exposure to cross-border operations, which may serve as channel for operational and/or financial distress. The proposed network representation can virtually accommodate these features; where some processes are undertaken in-house and the others outsourced.

Chapter 3

Interbank market structure, bank conduct, and performance: Evidence from the UK

3.1. Introduction

The interbank market is fundamental for the effective functioning of the financial system; banks provide liquidity support to each other towards sustaining themselves and the overall economy. Notwithstanding the pivotal role of the interbank market, I propose a novel cost. Given that banks compete against each other in the provision of loans to businesses in one (external) market, but provide loans to each other in the other (interbank) market, I argue that strategic spillovers between these two markets can generate an inefficient allocation of resources and consequently stimulate collusion and/or monopolistic pricing. Practically, banks are performance-driven institutions (Acharya, 2009), and their decisions are independently optimal but aggregately suboptimal (Dubecq et al., 2016). To achieve their goal of maximizing profits, which may be achieved not only by minimizing costs but also by maximizing revenues, banks tend to often adapt to market conditions. However, rather than employing independent firm specific characteristics, this chapter utilizes market-level conditions to gauge bank-level and interbank performance. Specifically, the prevailing market structure influences the conduct of banks, which consequently affects their performance. Surprisingly, the existing literature on interbank performance has so far made no provisions for interbank market structure and the role of bank conduct. Hence, this chapter extends Chapter 2 by incorporating the role of market structure and bank conduct in the interbank performance literature as championed by the SCP paradigm. Anti-competitive bank conduct in this chapter is defined as an agreement between two or more banks that is unenforceable in a court of law and aims at enhancing their competitive and/or comparative advantage via collusive and/or monopolistic pricing (Coulter et al., 2017).

The banking literature proposes two major hypotheses on the structure-conduct-performance (SCP) relationship in banking. Taken together, the implications for competition policy are in direct opposition: the market-power hypothesis is fundamental to antitrust policies/regulations while the efficient-structure hypothesis is rejected. The policy implications of the SCP paradigm are also relevant in the context of the interbank market and the UK banking system given the significant and ongoing structural changes in the banking industry. The SCP paradigm proposes that when a small group of firms dominate a market in terms of shares, the likelihood of collusive behaviour amongst these firms increases. In the interbank market setting, a clear evidence of this is the reported collusion by mandated global banks to deliberately manipulate the LIBOR (McConnell, 2013; Duffie and Stein, 2015; Coulter et al., 2017)[9]. These banks (1) low-balled their borrowing rates primarily to protect their reputation as creditworthy banks, and (2) colluded on their submissions to benefit their derivatives traders by lessening their losses (Abrantes-Metz et al., 2012; Schrimpf and Sushko, 2019). A bank's reputation is vital for determining its profitability and performance. When banks collude, they disrupt the relationship between bids and costs, with the objective of obtaining abnormal profits (Abranetz-Metz et. al., 2012). Simply, the higher the concentration in a market, the greater the chances of collusion and consequently, the higher the profitability performance of these firms.

Post financial crisis and the LIBOR scandal, several unconventional policy measures (e.g., bank consolidations, privatization, deregulation, among others) have been implemented by supervisory agencies to safeguard the banking sectors (Wheatley 2012; Afonso et al., 2019). Over the years, banks have repriced the risks associated with unsecured interbank lending, reflecting higher balance sheet costs due to tighter risk management and implementation of the new regulatory standards (Schrimpf and Sushko, 2019). Although these interventions have enhanced the interbank system, it also supports a highly consolidated as well as concentrated market structure (Bech and Monnet, 2016; Afonso et al., 2019). By 2010 UK-originated banks had been concentrated into four major banking conglomerates; Barclays, HSBC, Lloyds and the Royal Bank of Scotland with

[9] Between 2007 and 2012, investigations confirmed that global banks mandated to provide the British Bankers' Association with Libor quotes have been underestimating their true borrowing rates to signal soundness (Abranetz-Metz et al., 2012). First, these banks used their submissions to misrepresent their creditworthiness by understating their borrowing costs. Second, contributing trading desks colluded on their submissions in order to manipulate the Libor to favour their derivative positions (Duffie and Stein, 2015; Schrimpf and Sushko, 2019). The most prominent offenders, Barclays, Union Bank of Switzerland, Royal Bank of Scotland, JP Morgan, Citigroup, Bank of America, Deutsche Bank, and Rabobank, reached various settlements with the UK Financial Services Authority (Hou and Skeie, 2014).

several others who had limited ambitions or access to global capital markets becoming acquisition targets (Shabani et al., 2015). This created a fertile ground for greater collusion as banks continued to group together and use financial instruments to obtain mutual benefits with cost savings and increased profits (Silva et al., 2016). Specifically, bank collusion intensifies when two competing banks hold sufficient resources to provide business loans. For instance, to avoid competition in the interbank context, trading bank A gives trading bank B a loan, and this consequently leads to bank A not having adequate funds to compete with bank B. If these banks are large and have greater reach, bank B effectively becomes a monopolist making monopolistic profits by rationing the supply of loans (Corbae and Gofman, 2019). The interbank loan from A to B is a credible commitment device that stimulates anti-competive conduct. Bank A gains from this commitment through the receipt of a higher interest rate on the interbank loan, which embodies a portion of the monopolistic profits earned by bank B[10]. Simply, banks that are competitive in lending to the non-financial sector but lack the ability to generate funds can borrow funds from banks (their colluded counterparts) with excess of liquidity on the interbank market, and thus obtain the required funds to supply credit to the non-financial sector. Against this background, both banks would still be acting along their business lines that allow them to have a comparative advantage and thus have increased credit portfolios.

Moreover, Eisl et al. (2017) stress that the interbank reference rates are still susceptible to significant manipulation even under the current rate-setting process, given the greater concentration and collusion. Even when gains from interbank trade exist due to liquidity sharing, the welfare loss from collusion can outweigh the benefit (Corbae and Gofman, 2019). As such, bank profitability will continue to improve while cost efficiency reduces. Ostensibly, it seems rational to have profitable banking institutions, but what if the profits are being generated through monopolistic pricing? Examining whether monopoly pricing drives the relationship between interbank market concentration and performance has practical implications for antitrust policy interventions. For instance, if the consolidation

[10] The interest charged or surplus received by the bank lending in the interbank market is dependent on its bargaining power.

activities are driven by banks' motive to obtain monopolistic profits, then this may hurt the economy by making the interbank and intermediation process very costly.

Grounded on the above, this chapter sets out to examine whether the structure of the interbank market influences the behaviour/conducts of banks and ultimately their performance as captured via their profit and cost efficiencies. Banks engage in financial operations in the interbank market to manage their costs and/or to increase their profits. As such, collusion or monopolistic pricing may ensure that larger banks often have better investment opportunities both within and outside the financial network. These large banks may thus have no incentives to lend to or deal with non-large banks. Where they do, they may charge a substantial spread to maintain financial operations with non-large banks, particularly where they have to forgo external opportunities in favour of opportunities in the interbank market. Creditor banks may also charge an extra spread, particularly where the debtor is in a stressed position or where dealings occur at the end of the day, a period during which banks have little flexibility for adjusting their daily reserve requirements at the Central Bank (Silva et al., 2016). In this respect, I expect that, by participating in interbank funding and investment decisions, the interbank market structure should be a factor that explains not only bank cost and profit efficiency but also more importantly the conduct/behaviour of banks. I contend that, by engaging in interbank operations, banks can also change their behaviour. However, while it may be individually advantageous for banks to collude or monopolise financial networks for abnormal gains, the resulting global network structure –the aggregated decisions of all of the economic agents at once, and which has been proven to have a core-periphery structure – may be exposed to greater systemic risks.

The results support the validity of the SCP hypothesis by showing that interbank market structure provides a channel for banks operating in the UK to collude in the market for bank and business loans. Specifically, interbank market structure (i.e., the degree of interbank concentration) affects bank conduct or behaviour via collusive and/or monopolistic pricing, to consequently increase bank performance. Further, collusion and other anti-competitive behaviours in the interbank market exacerbate incentives for foreign and conglomerate banks to enter, although domestic banks can still make profits by supplying liquidity to small banks that enter but lack liquidity. Lastly, the results show that corporate governance matters significantly for the validity of the positive SCP hypothesis. Large bank boards are more likely to conduct/behave anti-competitive given their access to greater information, expertise, connections/affiliations and resources.

The study makes a number of contributions to the banking literature. First, this work fills a void by developing a SCP model for the interbank market. Despite the status of the London Interbank Market as a crucial liquidity house for banks and its rate benchmarking several key rates globally (Abrantes-Metz et al., 2012; McAndrews et al., 2017), to date, there has been no published work in this area. The results provide some insights on whether the interbank market structure has an effect on bank conduct and subsequently the performance (cost or profit efficiency) of trading banks. Second, this study adds to the literature about monopolistic/oligopolistic competition and collusion (e.g., Sannikov and Skrzypacz, 2007; Coccorese, 2009; Corbae and Gofman, 2019). The study shows how bank interactions and incentivized behaviour in one market may drive collusion in another market. This channel of collusion is distinct to evidence on industrial organizations given that non-financial institutions that are competitors cannot give "loans" to themselves, but financial institutions such as banks can. Third, given the conflict between the two competing SCP hypotheses, it is imperative to identify which appropriately explains interbank performance in the UK banking sector. Once identified, it can offer valuable policy implications for regulators.

Fourth, I overcome a key methodological problem of prior SCP studies (i.e., ignoring the role of bank conduct, and using the direct concentration-performance relation to confirm SCP) (see, Berger and Hannan 1989; Weiss and Choi, 2008). This study utilises an approach that incorporates the role of bank conduct in the structure-performance nexus to offer a valid confirmation of the SCP paradigm[11]. The SCP paradigm postulates that the market structure drives the behaviour/conduct of banks, which consequently impacts their performance. Thus, rather than using the direct concentration-performance regression, I introduce 'bank conduct' as the mediating variable between market structure and performance. As such, this study considers all three elements in the SCP paradigm (i.e., the structure, the conduct and the performance), a task yet to be achieved by traditional SCP literature. Fifth, in line with recent work and developments – i.e.,

[11] The approach mitigates the biases emphasized by prior works (e.g., Demsetz, 1973; Tirole, 1988). Whether higher bank performance or profitability is due to greater efficiency, collusion or product quality cannot be confirmed by merely relating market concentration to performance (or return) (Khan et al., 2018).

monitoring/scrutiny of consolidation activities – (Adams and Mehran, 2012; Srivastav and Hagendorff, 2016; Akbar et al., 2017), this study extends the narrow confines of the SCP by incorporating issues related to governance and reforms, and integrating UK's unique banking structure (i.e., ownership, consolidation and board structure). It is imperative for antitrust policy to examine whether these factors affect the SCP nexus. If they do, then antitrust interventions that focus solely on the traditional SCP tests may be inefficient. Overall, this study goes beyond the normal SCP regression model to provide a more sophisticated and legitimate test for both the market-power and the efficient-structure hypotheses in an interbank setting.

The rest of the chapter is organized as follows. Section 3.2 reports a review of the theory and literature on the SCP paradigm. Section 3.3 describes the data and methodology. Section 3.4 discusses the empirical results and other robustness tests. Section 3.5 offers conclusions of the chapter.

3.2. Literature review

3.2.1 The structure-conduct-performance (SCP) paradigm

The concept that market structure drives firm performance is grounded in the classical theory of the firm. Under a pure competitive model, an industry is characterized by a large number of firms which consequently intensifies market competition but decreases the concentration ratio (Smith, 1977). The decreased concentration ratio weakens firm profitability given the presence of product homogeneity and insignificant market shares of each firm. Overall, firms cannot dictate market price as concentration of market share is absent (Simon, 1991). Thus, productive efficiency is attained when price equates the minimum average total cost for firms to generate normal profits. Conversely, in a pure monopoly or monopolistic competitive model, firms hold significant market shares which empowers them to control product prices. Under this scenario, price surpasses the marginal cost/revenue for firms to generate sub-optimal production and/or supernormal profits (Krugman, 1979). Basically, the SCP assumes that a highly concentrated market share imply greater market power which enables banks to earn monopolistic profits

(Ricardian rent). In sum, a causal nexus runs from market structure to the price setting behaviour (conduct) of firms, and ultimately to profitability via the market power channel (Bain, 1951), hence, initiating the SCP paradigm.

The monotonic relation between market structure and firm performance is supported by extant empirical literature (e.g., Venaik et al., 2005; Weiss and Choi, 2008; Ralston et al., 2015). In the banking literature, the SCP paradigm is rooted in Mason (1939) and Bain's (1951) findings that greater market concentration enhances bank profitability. Specifically, the market structure (i.e., degree of concentration of banking firms) influences bank conduct or behaviour via collusive and/or monopolistic pricing, which consequently increase bank performance (Park and Weber, 2006; Webster, 2011; Mirzaei et al., 2013). A highly concentrated market engenders a lower degree of competition, which leads to market inefficiencies (e.g., monopolistic pricing and abnormal profits) (Homma et al., 2014).

Over the years, developments on the subject originated two competing testable hypotheses: the traditional SCP (market-power hypothesis) and the efficient structure hypothesis (ESH) (Berger et al., 2004). By the traditional SCP hypothesis (Gilbert, 1984; Hannan, 1991), a bank's profitability is driven by the market structure and level of competition. Specifically, higher market concentration grants more market power to banks which implies higher inefficiency (e.g., inability to minimize costs) without being forced out of the market (Fu and Heffernan, 2009). The lower (higher) the level of market competition (concentration), the higher the economic rent/profits for a bank. Hence, greater market concentration (i.e., market share) drives anti-competitive behaviours that are detrimental to consumers.

Like the SCP, the ESH also postulates a positive structure-performance nexus. However, the ESH stresses the role of efficiency in the SCP paradigm (Demsetz, 1973; Peltzman, 1977). As such, bank profitability or performance is explained by the degree of cost and/or technology efficiency (Smirlock, 1985; Weiss and Choi, 2008). Specifically, efficient firms (for e.g., due to low cost of production etc.) have greater market shares because they have the ability to charge lower prices without sacrificing profitability (Brozen and Bittlingmayer, 1982). That is, the higher profitability of large firms in concentrated markets is due to economies of scale and the greater efficiency level of large firms. In sum, the ESH stresses that superior firm efficiency drives greater market share regarding concentration, and is positively related to better performance. Bank efficiency should therefore represent the primary driver of market structure and performance because the most efficient banks will gain market share and earn higher economic profits (Evanoff and Fortier, 1988; Homma et al., 2014). Undeniably, both the traditional SCP and the ESH draws the same conclusion on a positive market power-profitability nexus. The key distinction, however, dwells on how market power can be attained in the first place. Hence, the traditional SCP treats market power as exogenous, which is driven by market concentration, whilst, the ESH treats market power as attained through high market share by sustaining or increasing firm-specific efficiency.

Very efficient banks often have superior management and technology to increase profitability and market share, which in turn increase market concentration and market power (Weiss and Choi, 2008). The ESH can be further segregated into the X-efficiency (ESX) and scale-efficiency (ESS) (Berger, 1995). The ESX structure stresses superior management, usage of superior technology, or other firm features that are imperative to firm success but are not equally distributed amongst all firms. Accordingly, banks that have better management and/or better technology (i.e., higher ESX) should have lower costs and higher profitability, which in turn should drive greater market shares and concentration (Peltzman, 1977; Fu and Heffernan, 2009). The ESS (Lambson, 1987), however, postulates that the competency of management and production technical levels are similar such that firms can only be differentiated based on economies of scale (Shepherd, 1983). Thus, a firm is scale efficient only if it operates at constant, rather than increasing or decreasing returns to scale[12] (Weiss and Choi, 2008). Specifically, banks that have optimal scale economies will tend to have lower costs and earn greater profits which will subsequently drive greater market share and concentration.

The key distinction between the SCP and the ESH rests in the differences in recommended policy interventions (Weiss and Choi, 2008; Khan et al., 2018). Where profitability is driven by market power, then anti-trust interventions may be socially beneficial, towards moving prices to competitive levels and attaining effective resource

[12] Banking institutions whose output levels are equivalent or similar to the minimum average cost/output may have superior scale efficiencies.

allocation. On the other hand, where greater efficiency drives profitability, then fragmenting efficient firms or restricting them from acquiring or merging with other firms may increase costs and consequently produce unfavourable product prices for consumers (Fu and Heffernan, 2009). Thus, believers of the traditional SCP treat antitrust and regulatory policy as socially beneficial whilst ESH proponents treat it as socially costly. Sheppard (1986) contends that market share and market efficiency combine to explain performance, whilst Smirlock et al., (1986) stress that the market share and monopoly power relation is blurry (Giorgis Sahile et al., 2015).

Because of the conflicting policy implications of the two hypotheses, prior studies (e.g., Smirlock, 1985; Mendes and Rebelo 2003; Fu and Heffernan, 2009) examine both simultaneously. Gilbert (1984) showed that both the SCP and the ESH are applicable to US banks. Berger and Hannan, (1989) also confirmed that both hypotheses may be compatible, at least in the short-term. Later, Lloyd-Williams et al., (1994) and Molyneux and Forbes, (1995) found evidence confirming the traditional SCP paradigm for Spanish banking and European banking. Berger (1995) also performed several tests on US banks and found limited support for both traditional SCP and ESH. Among European banks, Goldberg and Rai (1996) reported evidence confirming the SCP hypothesis -for banks operating in countries with very concentrated markets, and the ESX -for banks operating in countries with low concentration markets. Berger and Hannan (1998) found more evidence for the SCP paradigm among US banks while Maudos (1998) reported evidence for both the SCP and ESH among Spanish banks. Goddard et al., (2001) found support for both the SCP and the ESH hypotheses among banks operating in European countries. Among Portuguese banks, Mendes and Rebelo (2003) reported a swing from the traditional SCP during the early 1990s to the ESH after 1994. Among Chinese banks, Fu and Heffernan (2009) found significant evidence in favour of the traditional SCP as most banks operated below scale efficient levels. Khan et al., (2018) proved that the higher profits in concentrated banking industries are partially attributable to the anti-competitive conduct of ASEAN banks.

The notion that a financial network and its structure may influence bank efficiency is also shared across jurisdictions. Iori et al., (2008) argue that during the pre-crisis, changes in the interbank network structure incentivised banks to increase the number of banks they borrowed funds from but restricted the number of banks they were willing to supply credit to. The change in bank conduct or behaviour is attributed to liquidity shortages faced by smaller banks as a result of the increase in credit demand by the non-financial sector. In another breadth, Monticini and Ravazzolo (2014) show that interbank market frictions that resulted from the liquidity crises increased bank's ability to charge higher intraday interest rate spreads and thus, created the platform for abnormal gains through arbitrage. Similarly, Silva et al. (2016) find that the core-periphery structure of the interbank market is cost efficient for Brazilian banks, and thus encouraging greater participation of banks in financial networks. Nevertheless, the interbank market structure is inefficient in terms of risk-taking due to greater systemic risk exposures. These studies corroborate my contention that the interbank market structure influences bank conduct or behaviour via collusive and/or monopolistic pricing, and consequently resulting in improvement in the performance or efficiency level of banks.

3.3. Methodology

3.3.1. Data

I employ financial data on individual banks from the Orbis Bank Focus database (Bureau Van Dijk). The initial sample comprises 124 commercial banks in the UK. To stand a chance of inclusion in the analysis, the bank must have the data necessary to estimate cost and profit functions; and the data must span the period 2010 to 2018. I further exclude banks with no interbank loan data, leaving us with a final sample of 93 banks representing 75% of all the UK banks classified as commercial banks in Orbis. The sample year in this chapter has been extended by one year (from that in Chapter 2) to cover the additional year in the PhD. Nevertheless, the number of banks in the final sample remains unchanged and therefore suggesting that within the one year interval, no new banks have entered the UK interbank market. Even if some new banks did enter the UK interbank market, these new entrants failed to meet the inclusion requirement by not having the available data that spans between 2010-2018. The second-stage analysis utilises an unbalanced panel due to some missing observations for some of the control variables (see descriptive summary).

3.3.2. Estimation method

To empirically examine the mediating role of bank conduct, I follow Baron and Kenny's (1986) methodology. Baron and Kenny (1986) specified four assumptions that must be satisfied if market structure (concentration) explains bank performance via the conduct of the banks. These are (i) market structure must significantly drive bank conduct, (ii) bank conduct must significantly drive bank performance, (iii) market structure must drive bank performance in the absence of bank conduct, and (iv) the market structure effect on bank performance should reduce when the bank conduct variable is introduced into the estimation model. To empirically examine the effect of interbank market structure on bank conduct (i) and performance (ii) I utilise the model proposed by Berger et al. (2005) in Eqn. (3.1). I replace $Conduct_{i,t}$, the bank conduct measure, by $Performance_{i,t}$, the proxy for performance in Eqn. (3.2) to also explore the structure-performance paradigm. Eqn. (3.3) introduces both the structure and conduct measure into the estimation to test assumption (iii).

$$Conduct_{i,t} = \alpha + \beta_1 Structure_{i,t} + \beta_2 X_{i,t} + \omega_i + \mu_t + \varepsilon_{i,t} \quad (3.1)$$

$$Performance_{i,t} = \alpha + \beta_1 Structure_{i,t} + \beta_2 X_{i,t} + \omega_i + \mu_t + \varepsilon_{i,t} \quad (3.2)$$

$$Performance_{i,t} = \alpha + \beta_1 Structure_{i,t} + \beta_2 Conduct_{i,t} + \beta_3 X_{i,t} + \omega_i + \mu_t + \varepsilon_{i,t} \quad (3.3)$$

where *i* denotes the *i*th bank and *t* denotes fiscal year. X_{it} is the vector of the control variables, α and β are parameters, ω_i is a firm specific effect, and μ_t is a year fixed effect. To control for possible heteroscedasticity and autocorrelation within firms, the estimated standard errors of the regression coefficients are clustered at the firm level.

To validate the results, I also followed the literature (e.g., Goodman, 1960; Sobel, 1982; MacKinnon and Dwyer, 1993; MacKinnon et al., 1995; Khan et al., 2017) to verify the indirect effect of interbank market structure on bank performance. I estimate the Sobel, Aroian and Goodman test scores (z-value) to confirm the significance/insignificance of the indirect (mediated) effect. These tests utilise the product of the coefficient approach by estimating the product of two coefficients -outcome regressed on the mediator, and mediator regressed on the predictor - and testing them for significance. The null hypothesis to validate these tests requires that the indirect effect is not significantly different from zero. Although these test results are sometimes acceptable, they may not always work well when the indirect effects are positively skewed and kurtotic (Preacher and Hayes, 2004; Fritz et al., 2012). Consequently, the z-test and p-values for the indirect effects may not be reliable. Therefore, to obtain the asymmetric confidence intervals for the mediated effect, I proceeded to estimate the bootstrap standard errors and the percentile, bias-corrected, and bias-corrected and accelerated confidence intervals with 5,000 replications. A potential drawback of following the Baron and Kenny (1986) approach is the issue of potential endogeneity. However, these study focuses on testing the validity of the classical/traditional SCP model in the context of the interbank market.

3.3.3. Measurement of variables

3.3.3.1. Bank performance

Following Shaban and James (2018), this study applies parametric frontier techniques to measure bank-specific relative performance. The commonly used parametric technique – the Stochastic Frontier Approach (SFA) measures the efficiency with which banks utilise their inputs to produce a given set of outputs (Fu and Heffernan, 2009). Ultimately, the parametric techniques unlike the non-parametric techniques (e.g., DEA) allow for the specification of a stochastic term that mitigates any biases that arise from random events and measurement errors (Kumbhakar and Lovell, 2003; Shaban and James, 2018). I utilised the Battese and Coelli (1995) methodology to compute separate cost and profit efficiency scores for the sample of commercial banks. Specifically, I estimate the cost frontier as:

$$\ln C_{i,t} = f\left(q_{i,t}, w_{i,t}, t : \ \beta\right) + \left(\ln \gamma_{i,t} + \ln \mu_{i,t}\right) \quad (3.4)$$

$$i = 1, \dots \dots, N \ and \ t = 1, \dots \dots, T$$

where $\ln C_{i,t}$ represents the total cost of the *i*th bank at time *t*, $q_{i,t}$ is the vector of outputs, $w_{i,t}$ is the set of input prices, and *t* is the time trend incorporated to capture disembodied technical progress. β denotes the vector of unknown parameters to be estimated. The error term is segregated into two components (i.e., $\gamma_{i,t}$ and $\mu_{i,t}$) where $\gamma_{i,t}$ represents the autonomous and identically distributed random error that is expected to be independent of $\mu_{i,t}$ and distributed as $N(0, \sigma_{v,i}^2)$. The $\mu_{i,t}$ represents the inefficiency component which is a non-negative variable that captures the banks cost inefficiency and is autonomously distributed with truncation at zero. I estimated Eqn. (3.4) via the translog specification (see Eqn. (D1) in Appendix D). Traditionally, the inefficiency component and random error term can be multiplicatively separated from the estimated cost function.

The cost efficiency score is interpreted as the ratio of the actual cost incurred by the firm to the minimum attainable cost level given the cost frontier (see Eqn. (D2) in Appendix D). Simply, it is the percentage of costs/resources that have been utilised efficiently, such that a score of 0.90 would imply that a bank is 10% less cost efficient relative to the best-practice bank operating under the same conditions. I follow the bank performance literature (e.g., Duygun et al., 2013; Shaban et al., 2014) to measure and define the key variables in the cost frontier. Total operating costs (C_i) is the summation of interest expenses, salaries and employee benefits, and other operating costs. The output (q_i) variables comprise loans (q_1) measured as gross loans less any reserves allocated for non-performing loans; and securities investments (q_2). The input prices (w_i) comprise the cost of capital (w_1) measured as interest expenses scaled by total deposits (proxy for the price of funds or deposits); cost of physical capital (w_2) measured as overhead expenses (other than personnel expenses) scaled by book value of fixed assets (proxy for the price of fixed capital); and cost of labour (w_3) measured as personnel expenses scaled by number of employees (proxy for management quality or a more efficient use of labour). In order to ensure linear homogeneity, the dependent variable as well as the input prices are normalized (Shaban and James, 2018). Lastly, I incorporate a quasifixed input via the level of equity to control for differences in bank risk preferences (Berger and Mester, 1997; Shaban et al., 2014).

To measure a bank's relative profit efficiency, I use the Berger and Mester (1997) alternative profit frontier estimator. The standard assumption is that banks employ the given output quantities and input prices to maximize profits by adjusting the output prices and input quantities. Often, the alternative profit frontier is superior to the standard profit frontier especially where differences exist in the quality of the banking outputs and/or the output markets are not competitive (Shaban and James, 2018). Specifically, I estimate the profit frontier as:

$$\ln P_{i,t} = f\left(q_{i,t}, w_{i,t}, t :\ \beta\right) + \left(\ln \gamma_{i,t} + \ln \mu_{i,t}\right) \quad (3.5)$$

$$i = 1, \dots\dots, N \ and \ t = 1, \dots\dots, T$$

where $\ln P_{i,t}$ is profit before tax (PBT) for ith bank at time t; and $q_{i,t}$, $w_{i,t}$, $\gamma_{i,t}$ and t are outputs, inputs, random error, and time trend respectively. $\mu_{i,t}$ represents the inefficiency component which is a non-negative variable that enters the model with a negative sign. Thus, inefficiency should decrease profit. Following Shaban and James (2018), I mitigate the presence of negative profits (losses) in some of the sampled banks by transforming the dependent variable $P_{i,t}$ by estimating $P_{i,t}$ = $P_{i,t} + |(P)_{min}|$ where $(P)_{min}$ denotes the minimum absolute value of PBT over all sampled banks. Again, I estimate Eqn. (3.5) via the translog specification (see Eqn. (D3) and (D4) in Appendix D). Table 3.1 reports the summary statistics for the basic variables utilised to estimate the profit and cost efficiency scores.

Table 3.1: Variables used in profit and cost efficiency estimations

Variable	Mean	Median	St. Dev.	Minimum	Maximum	Obs
Profit (Cost) (*in thousand US $*)						
Total Profits	22080.118	1379.700	6190.715	-2270.000	243210.500	465
Total Costs	36174.731	210.344	9371.792	3.323	361330.906	465
Input Prices						
Cost of capital (w_1)	0.012	0.009	0.009	0.002	0.033	465
Cost of physical capital (w_2)	0.341	0.083	0.755	0.006	3.151	465
Cost of labour (w_3)	0.100	0.081	0.102	0.000	0.377	465
Output Prices (*in thousand US $*)						
Loans (q_1)	29755.103	956.840	8515.016	0.000	331000.000	465
Securities Investments (q_2)	12141.246	439.978	2973.740	0.000	119000.000	465

The table reports the summary statistics for the core variables utilised in the profit and cost efficiency estimations. In the translog estimations of profit (cost) efficiency, the input variables are: cost of capital, cost of physical capital, and cost of labour while the output variables are: loans, and securities investments. Total operating costs (C_i) is the summation of interest expenses, salaries and employee benefits, and other operating costs. The output (q_i) variables comprise loans (q_1) measured as gross loans less any reserves allocated for non-performing loans; and securities investments (q_2). The input prices (w_i) comprise the cost of capital (w_1) measured as interest expenses scaled by total deposits; cost of physical capital (w_2) measured as overhead expenses (other than personnel expenses) scaled by book value of fixed assets; and cost of labour (w_3) measured as personnel expenses scaled by number of employees. To mitigate any biases due to outliers, the data used have been winsorised at 1% to 99%.

From the estimated bank-level cost efficiency scores (CE score) and profit efficiency scores (PE score), I generate the bank-level cost efficiency ranks (CE rank) and profit efficiency ranks (PE rank) by ranking the CE and PE scores across all the sampled banks. Inherently, the efficiency ranks can more accurately signal the quality of the bank's management than can the scores (Berger et al., 2005). Theoretically, the efficiency scores range between zero and one [0,1], where one indicates the best-practice bank. Thus, I first ranked the banks based on their efficiency scores year-by-year. Subsequently, the bank that records the highest efficiency score in a fiscal year is ranked 1, and the bank with the lowest score ranked 93. Accordingly, the second stage analysis employed four key measures of relative performance. Where the dependent variables are the CE and PE rank, I estimate a censored Tobit regression; otherwise, the ordinary least squares (OLS) is used. A negative (positive) coefficient for any given explanatory variable in the cost or profit efficiency rank regression implies that an increase in this variable is associated with a higher (lower) efficiency rank. For robustness purposes, I also used standard financial ratios to measure profit and cost performance: net interest margin (NIM); return on average assets (ROA); return on average equity (ROE); and cost-income ratio (CIR). However, Berger et al., (2005) and Shaban and James, (2018) stressed that these ratios are less superior to the cost and profit efficiency scores and ranks.

3.3.3.2. Market structure

Market structure (level of competition) is often captured via the concentration indices based on the structural approach. Following Chang et al., (2008a, b), this study uses the Hirschman-Herfindahl index (HHI) and its dual (*d*) to measure the concentration of loans and borrowings on the interbank market. The HHI is the sum of the squares of the proportional market share of each participating bank in terms of interbank assets, and is specified as.

$$HHI_{it} = \sum_{i=1}^{n} \left(\frac{x_i}{x}\right)^2 \quad (3.6)$$

where *n* denotes the number of banks; x_i represents the absolute participation of bank *i;* and *x* represents the total volume of the banking market, $x = \sum_{i=1}^{n} x_i$. Using the squares of the relative market share of each bank’s interbank assets account for the size of institutions: larger size implies greater market power. The HHI ranges between 0 and 1 in the case of monopoly. Under a perfect competition setting, HHI reaches its minimum value, $1/n$, and tends toward zero when the number of banks (n) is greater, with HHI>0.18 implying high concentration; 0.1<HHI<0.18 implying moderate concentration; and HHI<0.1 implying no concentration.

To mitigate any biases associated with the HHI (e.g., failure to directly incorporate the number of banks), this study uses the HHI dual as a clearer and more objective measurement of interbank concentration. The dual provides a proportion of banks that dominated the interbank market (see Chang et al. (2008) for further discussion on the superiority of the dual against the HHI).

The HHI dual epitomises a theoretical market that has similar features as the real market, regarding the number of participants n and the total volume of the market (Chang et al., 2008). However, the theoretical market is stratified into two groups. The first is the dominant group, comprising k banks with equally distributed shares and that holds total participation of the market. The second group comprises $n-k$ banks that do not have participation in the market. The total volume of the theoretical market equates to the total volume of the real market, and thus the HHI of these two markets are equal ($HHI_{MT} = HHI_{MR}$).

Grounded on the above, the Herfindahl–Hirschman dual (d) is the percentage $d = 1 - \frac{k}{n}$, which captures the percentage of banks that have no market participation. Chang et al. (2008) proves that $k = \frac{1}{HHI_{MR}}$; thus, $d = 1 - \frac{1}{nHHI_{MR}}$, where n denotes the number of banks and HHI is the Herfindahl–Hirschman index of the banks. Simply, the dual, d, shows the proportion of banks that have no market participation, or equivalently, the fraction, $1 - d$, for banks that take hold of or dominate the entire interbank market. As the dual (d) increases, the HHI also increases. The dual (d) is an increasing function of the HHI and since HHI ranges between $1/n$ to 1, the minimum of d is zero (perfect competition) and the maximum is $1 - \frac{1}{n}$ (monopoly). The dual approximates to 1 when n is large implying a high degree of concentration. For robustness purposes, I also use the 5-firm concentration (CR5) which is calculated as the total interbank assets of the five largest banks to the total interbank assets of all banks on the interbank market. The degree of concentration in the interbank market is expected to have a negative effect on competition in the market, and thus increase (decrease) the profit (cost) performance of banks.

3.3.3.3. Bank conduct

I follow prior studies (e.g., Bikker and Haaf, 2002; Staikouras and Koutsomanoli-Fillipaki, 2006; Delis, 2010) to measure the conduct of banks. I use the Panzar–Rosse H-statistic (PRH) to gauge the competitive or non-competitive conduct of banks. The Panzar–Rosse model (Panzar and Rosse, 1982, 1987; Rosse and Panzar, 1977) measures the transfer of changes in input prices to revenue. Higher (lower) transmission values indicate greater competitive (market power) pricing. The PRH statistic is derived by summing the elasticities of the bank's revenue with respect to all input prices. In a profit maximization setting, PRH must be equal to one (PRH = 1) for perfect competition, less than or equal to zero (PRH ≤ 0) for monopolistic competition, and between 0 and 1 (0 > PRH > 1) for oligopolistic competition.

I use the unscaled revenue model (Bikker et al., 2012) to estimate the PRH as:

$$\ln TR_{i,t} = \alpha + \beta_1 \ln W_{i,t} + \beta_2 X_{i,t} + \omega_i + \mu_t + \varepsilon_{i,t} \tag{3.7}$$

where $TR_{i,t}$ the total revenue of the ith bank in time t; $w_{i,t}$ is the set of input prices (i.e., the cost of capital (w_1); cost of physical capital (w_2); and cost of labour (w_3)); X_{it} is the vector of the control variables; ω_i is a firm specific effect; μ_t is a year fixed effect and $\varepsilon_{i,t}$ is the random error. The bank-level controls are the ratio of customer loans to total assets, the ratio of non-earning assets to total assets, the ratio of customer deposits to total funding, and the ratio of total equity to total assets (credit risk), asset composition, interbank funding mix and leverage. The summation of coefficients (β) on the three input prices gives the PRH statistic.

Bikker et al. (2012) suggest that the standalone PRH values are insufficient for assessing the competitive conduct of banks. Accordingly, I also estimate the revenue model based on the intermediation approach and using the bank's total income as dependent variable in Eqn. (3.7).

$$\ln TI_{i,t} = \alpha + \beta_1 \ln W_{i,t} + \beta_2 X_{i,t} + \omega_i + \mu_t + \varepsilon_{i,t} \quad (3.8)$$

Where the output, $TI_{i,t}$ denotes the natural logarithm of total income, which includes interest and non-interest income; $w_{i,t}$ is the set of input prices (i.e., the cost of capital (w_1); cost of physical capital (w_2); and cost of labour (w_3)); X_{it} is the vector of the control variables; ω_i is a firm-specific effect; μ_t is a year fixed effect and $\varepsilon_{i,t}$ is the random error. The bank level controls are same as in Eqn. (3.7).

For robustness purposes, I also employed the Price–Cost Margin (PCM) based on the Net Interest Margin (NIM) and the adjusted Lerner Index as alternative proxies for bank conduct. The NIM echoes the pricing ability of banks for services, deposits and loans (Goldberg and Rai, 1996; Khan et al., 2018). Where the SCP hypothesis indicates anti-competitive pricing, then banks should charge lower deposit rates and/or charge higher loan rates (Berger and Hannan, 1989). Given that banks are capable of pricing their products anti-competitively, then a higher NIM is expected to indicate the bank's pricing ability. We follow Gaspar and Massa (2006) to estimate the PCM based on NIM as:

$$PCM1_{i,t} = NIM_{i,t} - NIM_{TW,t} \quad (3.9)$$

where $NIM_{i,t}$, is the net interest margin of the *i*th bank in time *t*, and $NIM_{TW,t}$ is the turnover-weighted average of industry net interest margin. Turnover is the sum of interest income and noninterest income. For an individual bank, the net interest margin is the net income scaled by the sum of interest income and noninterest income.

Market power also signals a bank's ability to set prices (P^p) above marginal cost (MC) (Lerner, 1934). The Lerner Index measures the competitive conduct of banks. In a perfectly competitive market, P^p and MC are equal; while less competitive markets are characterised by greater divergence between P^p and MC. The conventional Lerner Index expressed as the difference between P^p and MC, scaled by the P^p for bank *i* at time *t* is:

$$Lerner_{it} = \frac{P^p{}_{i,t} - MC_{i,t}}{P^p{}_{i,t}} \quad (3.10)$$

where $P^p{}_{i,t}$ denotes the price of the output, and $MC_{i,t}$ is the marginal cost of producing an additional unit of output. The difference between a firm's/bank's price ($P^p{}_{i,t}$) and marginal cost ($MC_{i,t}$) reflects the extent of market power a firms/bank may possess. The bank's total assets represent its output, and hence the price of total assets is equal to total revenue scaled by total assets. The Lerner Index ranges between 0 (perfect competition) and 1 (the inverse of price elasticity of demand implying monopoly or collusion). Thus, higher Lerner values imply greater market power and less competitive conditions.

The $MC_{i,t}$ can also be derived from the translog cost function (see Eqn. (D5) and (D6) in Appendix D). Once D6 is estimated, it is subsequently utilised to calculate the Lerner Index for individual banks via Eqn. (3.10). However, to mitigate any biases associated with the above estimation (i.e., Eqn. 3.10) (e.g., the implicit assumption of full bank efficiency and not accounting for the likelihood of banks failing to fully exploit output pricing opportunities due to market power - Amidu, 2013), I follow Koetter et al., (2012) to adjust the Lerner Index (PCM2) using Eqn. (3.11).

$$PCM2_{i,t} = Lerner_{it} = \frac{\pi_i + tc_i - mc_i * q_i}{\pi_i + tc_i} \tag{3.11}$$

where π_i, tc_i, $mc_i$and q_i represent the profit, total cost, marginal cost and output respectively of the bank 'i'. The adjusted Lerner ($PCM2_{i,t}$) values also range between 0 and 1, with higher values implying greater market power.

3.3.3.4. Control variables

In line with the banking literature (Fu and Heffernan, 2009; Williams, 2012; Mirzaei et al., 2013; Khan et al., 2018), I control for bank-level and board-specific variables that are likely to affect SCP. These include bank size, market share, ownership, off-balance-sheet activities (OBS), risk, bank age, conglomerates, and board size. Bank age highlights the reputation that a bank openly transmits to the market, and also serves as a proxy to capture the length of lending relationships between lending banks on the interbank market (e.g., Anand et al., 2015; Bräuning and Fecht, 2016). To achieve performance goals, banks tend to adapt to market changes, which may not necessarily be driven by prior relationships. However, where prior relationships are imperative, longer lending relationships between lending banks may mitigate information asymmetry between borrowing banks and their suppliers of funds, and thus, enabling older banks to lend or borrow funds towards achieving their performance objectives. Longer lending relationships may also create a fertile ground for collusion or monopolistic pricing may ensure that older banks often have better investment opportunities both within and outside the financial network. For instance, Degryse and Van Cayseele, (2000) found that older banks charge lower interest rates and this effect is primarily driven by the lock-in effect of a bank-firm relationship. Similarly, prior studies (e.g., Berger et al., 2001; Hernández-Cánovas and Martínez-Solano, 2010) found that it is less costly for lenders to obtain information about large banks or those with a long history. Therefore, a lender that is large or older should be more likely to use the unsecured interbank market for loans. A summary of all the key variables used in the main analyses and their descriptions is reported in Table 3.2.

Table 3.2: Definition of variables

Variable	Definition
Performance Measures	
PE SCORE	Profit efficiency score
PE RANK	Profit efficiency rank
CE SCORE	Cost efficiency score
CE RANK	Cost efficiency rank
NIM	Net interest margin
ROA	Return on average asset
ROE	Return on average equity
CIR	Cost-income ratio
Structure Measures	
HHI	Herfindahl–Hirschman Index (HHI) is the sum of the squares of the proportional market shares of each bank in the interbank market.
HHI Dual	HHI Dual defines the percentage of banks that have no participation in the interbank market. It is measured as $d = 1 - \frac{k}{n}$, where $k = \frac{1}{HHI_x}$ and symbolises the fraction of the banks that do not have interbank market participation. Hence, $d = 1 - \frac{1}{n.HHI_x}$, where n is the number of banks. Equally, *1 – d* is the fraction of banks that dominate the entire market.
CR5	CR5 is the five-bank concentration ratio based on the market shares of the five largest banks in the loan market.
Conduct Measures	
PRH1	PRH1 is the Panzar–Rosse H-statistic statistic based on the unscaled total revenue.
PRH2	PRH2 is the Panzar–Rosse H-statistic statistic based on total income.
PCM	PCM is the Price–Cost Margin based on the net interest margin.
PCM2	PCM2 is the Price–Cost Margin based on the adjusted Lerner Index.
Control Variables	
Bank Size	The natural logarithm of the book value of total assets.
Market Share	The ratio of the loan total of each bank in the loans market to the total of loans of all the banks in the sample.
Ownership	An indicator variable equal to one if a bank is domestically owned, zero otherwise (foreign owned).
OBS Activity	This is the ratio of off-balance sheet activities scaled by total bank assets.
Risk	Tier 1 capital scaled by risk-weighted assets. This measure is homogeneous across banks and underpins the regulatory capital calibration in international standards. It captures the risk of default of a bank, and indeed serves that purpose in stress testing exercises.
Bank Age	The natural logarithm of the time between the incorporation year of a bank and the end of the fiscal year.
Conglomerate	An indicator variable equal to one if the bank is affiliated with a conglomerate, 0 otherwise.
Board Size	The natural logarithm of the total number of directors on the board as at the end of the fiscal year.

The table presents the mnemonics and definition of each variable used in this chapter.

3.4. Results and Discussion

The chapter aims to empirically examine the effect of interbank market structure on bank conduct and performance. As stated earlier, this study follows Berger et al. (2005) to first generate the robust relative performance measures of cost and profit efficiency scores estimated via the cost and alternative profit functions, respectively. The second stage of the analysis involves the estimation of three sets of models, where dependent variables are either bank conduct or performance (with and without mediation) indicators. I use the Tobit censored regression model where the efficiency ranks (CE or PE) serve as the dependent variable, and OLS otherwise. As specified earlier, the validity of the SCP relies on four conditions: (i) market structure must significantly drive bank conduct, (ii) bank conduct must significantly drive the bank performance, (iii) market structure must drive bank performance in the absence of the bank conduct, and (iv) the market structure effect on bank performance should reduce when bank conduct variable is introduced into the estimation model. I discuss the estimation results of each condition in the subsequent sections.

3.4.1. Descriptive statistics and bivariate correlations

This section reports the summary statistics of all the variables in the empirical analysis before proceeding to discuss the core findings in subsequent sections. Table 3.3 shows the descriptive statistics of the variables used in the estimation of Eqns. (3.1), (3.2) and (3.3). The average profit efficiency score is 0.80 with a standard deviation of 0.40, indicating limited disparities in terms of profit efficiency amongst the sample of UK banks. For cost efficiency, I observe an average score of 0.52 with a slightly lower standard deviation of 0.22. The accounting-based profitability measures show a healthy, profitable banking sector with average NIM, ROA and ROE of 5.70%, 2.42%, and 5.00% respectively. For the market structure indicators, the results show a less concentrated interbank market with average HHI, HHI dual and CR5 of 0.07, 0.85 and 0.33 respectively. These measures also have standard deviations of 0.00, 0.01 and 0.28 respectively. For the bank conduct indicators, the average PRH based on total revenue and total income is 0.14 and 0.05 respectively, with a standard deviation of 0.00 and 0.08 respectively. This implies that firms may attempt to engage in collusion rather than competing to gain higher profits over the long-term. The average PCM based on the NIM and the adjusted Lerner is 0.60 and 0.27 respectively, implying anti-competitive pricing by banks. Regarding the control variables, the results indicate that the mean value of bank size is 15.72 with a standard deviation of 2.48 implying the presence of large banks with limited disparities. Average market share is 0.11 with standard deviation of 0.03 signifying a lower degree of heterogeneity. Average bank risk is 0.20 with a standard deviation of 0.03 suggesting a low degree of heterogeneity. Average OBS activities is 12.75 with standard deviation of 3.33 signifying a fair degree of heterogeneity.

Table 3.3: Descriptive statistics

Variable	Mean	Median	St. Dev.	Minimum	Maximum	Obs.
<u>Performance Measures</u>						
PE SCORE	0.799	1.000	0.400	0.290	1.000	465
CE SCORE	0.518	0.569	0.219	0.165	0.857	465
PE RANK	47.000	47.000	26.845	1.000	93.000	465
CE RANK	47.000	47.000	26.845	1.000	93.000	465
NIM	5.702	5.320	2.860	-1.460	12.710	465
ROA	2.417	1.350	2.805	-5.406	14.708	465
ROE	5.004	3.600	3.168	-10.990	26.770	465
CIR	64.932	61.140	57.706	27.100	1.325	465
<u>Structure Measures</u>						
HHI	0.073	0.073	0.005	0.068	0.081	8
HHI Dual $(1 - d)$	0.850	0.850	0.009	0.841	0.866	8
CR5	0.327	0.247	0.283	0.077	0.859	8
<u>Conduct Measures</u>						
PRH1	0.139	0.139	0.000	0.139	0.139	8
PRH2	0.045	0.065	0.077	-0.101	0.102	8
PCM	0.603	0.723	0.663	0.709	0.962	465
PCM2	0.265	0.207	0.199	0.187	0.364	465
<u>Control Variables</u>						
Bank Size	15.723	15.239	2.476	10.641	21.516	465
Market Share	0.110	0.000	0.026	0.000	0.157	465
Ownership	0.247	0.000	0.432	0.000	1.000	465
OBS Activity	12.752	12.765	3.331	2.833	20.008	465
Risk	0.200	0.000	0.028	0.000	0.450	465
Bank Age	3.502	3.367	0.994	1.386	5.844	465
Conglomerate	0.699	1.000	0.459	0.000	1.000	465
Board Size	4.364	4.205	0.982	1.792	6.315	465

The table presents the summary statistics for all variables used for the core analysis. All variable definitions are in Tables 3.2. To mitigate any biases due to outliers, all control variables have been winsorised at 1% to 99%.

Table 3.4 reports the correlation between all the variables employed in the analysis. I observe that the correlations between the key performance indicators (PE score, CE score, PE rank and CE rank) are high. Thus, indicating that these indicators capture a similar construct (performance). Similarly, the correlation coefficient between the three structure measures (HHI, HHI Dual, and CR5) are high indicating that these variables also capture similar information (market structure). A preliminary insight into the relationship between the performance measures and structure is also illustrated by the correlation matrix. I observe that the correlation between the performance and structure measures is positive (score) or negative (ranks) and significant at the one percent (1%) level. For the structure-conduct and conduct-performance preliminary tests, I observe a negative (PRH) or positive (PCM) structure-conduct relation, as well as a negative (score) or positive (rank) conduct-performance relation. Regarding the control variables, the correlation among them shows that there is no issue of multicollinearity. In general, the findings from both descriptive summary and the correlation matrix suggest that none of the variables suffer from any momentous biases (e.g., limited variation and heterogeneity or large outliers) that may likely plague the regression results.

Table 3.4: Correlation matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1	PE score	1.00																						
2	CE score	0.86*	1.00																					
3	PE rank	-0.88*	-0.93*	1.00																				
4	CE rank	-0.83*	-0.98*	0.96*	1.00																			
5	NIM	0.02	0.08	-0.04	-0.10	1.00																		
6	ROA	0.23*	0.24*	-0.20*	-0.21*	0.07	1.00																	
7	ROE	0.18*	0.22*	-0.20*	-0.21*	0.12	0.61*	1.00																
8	CIR	0.10	0.13*	-0.13*	-0.13*	0.08	0.46*	0.60*	1.00															
9	HHI	0.08	0.03	0.09	0.02	0.02	0.08	0.03	-0.03	1.00														
10	HHI Dual	0.07	0.02	0.08	0.02	0.02	0.07	0.03	-0.03	0.99*	1.00													
11	CR5	0.10	0.03	0.11	0.03	0.02	0.08	0.03	-0.03	0.99*	0.98*	1.00												
12	PRH	-0.17*	-0.06	0.12	0.06	0.02	0.00	-0.03	-0.02	-0.10	-0.13*	-0.03	1.00											
13	PRH2	-0.07	-0.03	0.08	0.03	0.03	-0.07	0.04	0.02	-0.61*	-0.60*	0.58*	0.07	1.00										
14	PCM	-0.07	-0.01	0.06	0.01	0.04	0.00	0.02	-0.01	0.02	0.02	0.09	0.12*	0.37*	1.00									
15	PCM2	-0.12*	-0.01	0.08	0.01	0.09	-0.03	-0.09	0.08	0.26*	0.25*	0.30*	0.19*	0.21*	0.15*	1.00								
16	Bank Size	0.33*	0.14*	-0.22*	-0.08	-0.32*	-0.04	0.07	-0.10	0.01	0.01	0.01	-0.01	0.00	0.01	-0.24*	1.00							
17	Market Share	0.31*	0.11	-0.19*	-0.08	-0.24*	-0.02	0.02	-0.03	-0.00	-0.00	-0.00	0.00	0.00	-0.00	-0.17*	0.61*	1.00						
18	Ownership	0.20*	0.15*	-0.16*	-0.11	0.29*	0.01	0.05	-0.05	0.00	0.00	0.00	0.00	0.00	0.00	-0.06	0.34*	0.23*	1.00					
19	OBS Activity	0.29*	0.17*	-0.23*	-0.13*	-0.20*	-0.04	-0.03	0.00	-0.00	-0.00	-0.00	-0.01	0.00	0.00	-0.17*	0.58*	0.50*	0.38*	1.00				
20	Risk	-0.05	-0.06	0.05	0.04	-0.03	0.02	-0.01	-0.04	0.01	0.01	0.01	0.03	0.03	0.06	0.05	-0.08	-0.03	-0.05	-0.05	1.00			
21	Bank Age	0.26*	0.16*	-0.18*	-0.11	-0.08	0.04	0.05	-0.04	-0.04	-0.04	-0.05	-0.03	0.04	-0.02	-0.17*	0.50*	0.35*	0.41*	0.41*	-0.04	1.00		
22	Conglomerate	0.26*	0.19*	-0.20*	-0.13*	-0.22*	0.01	-0.04	0.06	0.00	-0.00	0.00	0.00	0.00	0.00	-0.16*	0.56*	0.25*	0.16*	0.45*	0.02	0.40*	1.00	
23	Board Size	0.17*	-0.03	-0.01	0.09	-0.22*	0.09	0.03	-0.03	0.00	-0.00	0.00	0.00	0.00	0.00	-0.21*	0.60*	0.43*	0.18*	0.41*	-0.04	0.52*	0.45*	1.00

The table presents the unconditional correlation coefficient between any pair of variables. All variables are as described in Table 3.2. * Indicates significance at 1%.

3.4.2. Market structure and bank conduct

In Table 3.5, I report the empirical results for the first condition of the SCP paradigm. Bank conduct is captured via the PRH statistic and PCM with models 1-3 (4-6) and 7-9 (10-12) reporting the results for PRH based on total revenue (total income) and PCM based on NIM (adjusted Lerner) respectively. All models incorporate firm fixed effects, time dummies and clustering at firm level. The results show that market structure has a negative and statistically significant impact on bank conduct (PRH) at the 1% level. Given that higher PRH values imply greater competitive conduct or pricing of banks, the negative coefficients on the market structure indicators suggest that greater interbank concentration leads to less competitive conduct or pricing by the banks.

The results under the alternative conduct measures (PCM) in models 7-12 provide strong support for the key implications of the market structure-bank conduct nexus in the main analysis. The results show a positive and statistically significant impact of structure indicators on bank conduct (PCM) at the 1% level. However, because higher PCM values indicate anti-competitive pricing by banks, the positive market structure-bank conduct nexus imply that banks behave anti-competitively when interbank market concentration surges. These findings confirm the position of Bikker and Haaf (2002) and Khan et al., (2018) that higher market concentration should stimulate anti-competitive pricing (conduct) by the banks. Iori et al. (2008) find that changes in the interbank network structure during the pre-crisis incentivised banks to increase the number of banks they borrowed funds from but restricted the number of banks they were willing to supply credit to.

Regarding the control variables, I find that a number of characteristics such as bank size, market share and conglomeration stimulate anti-competitive bank conduct or behaviour. This is in line with previous empirical studies (e.g., Webster, 2011; Mirzaei et al., 2013) and theoretical predictions that suggest that where banks that hold a significant market share, a key characteristic of large banks or conglomerate, they possess substantial market power in pricing. However, bank risk taking is related to competitive bank behaviour.

Overall, I show that the interbank market structure significantly affects the bank conduct. The evidence suggests that, where the SCP hypothesis indicates anti-competitive (collusive and/or monopolistic) pricing, then the banks may often have better investment opportunities both within and outside the financial network. These banks may often have no incentives to lend to or deal with smaller banks. Where they do, they may charge a substantial spread to maintain financial operations with non-large banks, particularly where they have to forgo external opportunities in favour of opportunities in the interbank market. In addition, trading banks that are competitive in lending to the non-financial sector but lack the ability to generate funds can borrow funds from their colluded counterparts with excess liquidity on the interbank market, and thus obtain the required funds to supply credit to the non-financial sector. Against this background, both banks would still be acting along their business lines that allow them to have a comparative advantage and thus have increased credit portfolios. The findings also confirm that theoretically and empirically interbank markets provide a channel for banks to collude in the market for business loans (Corbae and Gofman, 2019).

Table 3.5: Market Structure and Bank Conduct

	PRH			PRH2			PCM			PCM2		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
HHI	-0.270***			-0.192***			0.260***			0.215***		
	(0.000)			(0.000)			(0.000)			(0.003)		
HHI Dual		-0.147***			-0.104***			0.141***			0.117***	
		(0.000)			(0.000)			(0.000)			(0.002)	
CR5			-0.388***			-0.275***			0.373***			0.308***
			(0.000)			(0.000)			(0.000)			(0.004)
Bank Size	-0.022	-0.017	-0.032	-0.032	-0.010	-0.009	0.599	0.680	0.231	0.116	0.116	0.116
	(0.036)	(0.047)	(0.021)	(0.039)	(0.026)	(0.013)	(0.468)	(0.561)	(0.179)	(0.073)	(0.073)	(0.073)
Market Share	-1.888	-1.832	-0.082	-1.063	-0.113	-0.300	2.953***	3.178***	2.035**	0.142***	0.142***	0.142***
	(1.870)	(2.786)	(0.931)	(2.024)	(1.640)	(0.659)	(0.215)	(0.257)	(0.994)	(0.018)	(0.018)	(0.018)
Ownership	-0.044	-0.077	0.025	-0.029	-0.033	0.024***	0.624***	0.759***	0.131	0.071***	0.071***	0.071***
	(0.075)	(0.130)	(0.040)	(0.059)	(0.065)	(0.012)	(0.209)	(0.268)	(0.227)	(0.002)	(0.002)	(0.002)
OBS Activity	-0.004	0.005	0.021***	-0.016	0.011*	0.003***	0.217***	0.261***	0.020***	-0.007	-0.007	-0.007
	(0.010)	(0.015)	(0.006)	(0.012)	(0.006)	(0.000)	(0.108)	(0.110)	(0.008)	(0.018)	(0.018)	(0.018)
Risk	1.459	0.426	1.174	0.104	0.992***	0.386**	-3.513***	-3.353***	-3.203***	-0.537	-0.537	-0.537
	(1.677)	(2.723)	(2.009)	(0.173)	(0.125)	(0.181)	(0.433)	(0.488)	(0.392)	(0.410)	(0.410)	(0.410)
Bank Age	0.048	0.004	-0.089***	0.089**	-0.063*	-0.017	-1.021***	-1.277***	0.150	0.033***	0.033***	0.033***
	(0.044)	(0.071)	(0.025)	(0.038)	(0.035)	(0.019)	(0.374)	(0.422)	(0.135)	(0.011)	(0.011)	(0.011)
Conglomerate	-0.052	-0.062	-0.136**	-0.044	-0.020	-0.021	0.180	0.035	0.730***	0.077	0.077	0.077
	(0.091)	(0.144)	(0.057)	(0.072)	(0.075)	(0.050)	(0.618)	(0.786)	(0.245)	(0.204)	(0.204)	(0.204)
Board Size	-0.034	-0.018	0.043	-0.051	0.033	0.008	0.613	0.766	-0.087	-0.189	-0.189	-0.189
	(0.047)	(0.073)	(0.033)	(0.049)	(0.037)	(0.024)	(0.451)	(0.511)	(0.175)	(0.139)	(0.139)	(0.139)
Constant	2.272***	1.278***	1.956***	1.456***	8.906***	1.232***	-9.339***	-1.945***	-9.035***	-1.526***	-0.989***	-1.276***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	465	465	465	465	465	465	465	465	465	465	465	465
r2	0.818	0.818	0.818	0.898	0.898	0.898	0.921	0.921	0.921	0.214	0.214	0.214
N_clust	93	93	93	93	93	93	93	93	93	93	93	93

This table presents the estimated results for the structure-conduct relationship. All specifications include year and firm fixed effects. Standard error robust to heteroscedasticity and clustering at firm level are given in parentheses. Significance indicators: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.4.3. Market structure and bank performance

In this section, I examine whether the interbank market structure should matter more for bank performance, independent of bank conduct. Table 3.6 reports the results of the performance model (Eqn. 3.2) based on the efficiency scores and ranks estimated from the frontier models. In terms of the structure effect on profit efficiency performance, the significant and positive sign of the coefficient on the structure measures in the PE and CE score regressions indicate that market structure is associated with profit efficiency gains. This finding is further supported by the negative and significant coefficient on the structure measures in the PE and CE rank regressions. This suggests that greater interbank market concentration is associated with both high profit and cost efficiency rank of trading banks.

Furthermore, Table 3.7 reports the results where profitability and efficiency ratios are dependent variables. Among the accounting performance indicators, I observe a positive and significant concentration–profitability nexus. Market structure is associated with higher NIM, ROE and ROA. The negative and statistically significant coefficient in the CIR regression suggests that banks tend to be more efficient in managing their overhead costs relative to income[13]. These findings are consistent with prior studies which utilise analogous concentration and profitability indicators (e.g., Al-Muharrami and Matthews, 2009; Tregenna, 2009). Nevertheless, the validity of the SCP tests in these studies seem inadequate given that they construed the positive concentration–profitability nexus as adequate confirmation of the SCP hypothesis. I also confirm the position of Corbae and Gofman (2019) that interbank market entry surges when bank profits are low relative to entry costs, but entry declines when bank profits are high. In sum, collusion in the interbank market incentivises banks to enter, with the goal of improving their profit and cost efficiency and/or performance. As noted in Silva et al. (2016), the interbank market structure is cost efficient for banks, and thus encourages greater participation of banks in financial networks.

Regarding the control variables, market share is consistently positive (negative) and significant on the efficiency scores (ranks). This confirms the position of Khan et al.

[13] CIR captures the extent to which operating expenses (i.e., overheads) absorb operating revenues. A lower CIR ratio implies greater bank efficiency in management of overhead costs relative to income.

(2018) and Shaffer and Spierdijk (2019) that market share reflects the effects of product differentiation. Hence, banks associated with higher quality products should have superiority in charging higher prices and also earn higher profits to enable them secure greater market shares. Bank size also shows a consistently positive coefficient on PE indicating that larger banks gain from economies of scale, diversification and market power to earn superior profits: they borrow and/or lend at more favourable terms (Cocco et al., 2009; Acharya et al., 2012). The negative (positive) coefficient on CE score (rank) implies that larger banks have lower levels of cost efficiency.

Table 3.6: Market Structure and Performance

	PE SCORE	PE RANK	PE SCORE	PE RANK	PE SCORE	PE RANK	CE SCORE	CE RANK	CE SCORE	CE RANK	CE SCORE	CE RANK
HHI	0.115***	-0.183***					0.373***	-0.232***				
	(0.000)	(0.000)					(0.000)	(0.000)				
HHI Dual			0.624***	-0.930***					0.202***	-0.117***		
			(0.004)	(0.004)					(0.000)	(0.000)		
CR5					0.165***	-0.348***					0.535***	-0.312**
					(0.003)	(0.001)					(0.138)	(0.142)
Bank Size	0.086***	0.110	0.116**	0.122	0.088***	0.093	-0.421***	0.310***	-0.421***	0.310***	-0.421***	0.311***
	(0.010)	(0.252)	(0.060)	(0.252)	(0.005)	(0.212)	(0.111)	(0.098)	(0.111)	(0.098)	(0.111)	(0.099)
Market Share	0.425	-0.016	0.136	-0.052	0.162	-0.379	0.704	-2.676	0.704	-2.681	0.704	-2.685
	(0.727)	(0.127)	(0.404)	(0.124)	(0.219)	(1.059)	(0.740)	(4.122)	(0.740)	(4.120)	(0.740)	(4.136)
Ownership	-0.075*	-0.034	-0.023	-0.035	0.101***	-0.275***	0.798**	-0.430	0.798**	-0.430	0.798**	-0.430
	(0.032)	(0.024)	(0.192)	(0.025)	(0.014)	(0.019)	(0.322)	(0.266)	(0.322)	(0.266)	(0.322)	(0.265)
OBS Activity	-0.024	-0.014	-0.007	-0.014	-0.061***	-0.011	0.160***	-0.084***	0.160***	-0.084***	0.160***	-0.084***
	(0.036)	(0.010)	(0.018)	(0.010)	(0.002)	(0.009)	(0.056)	(0.027)	(0.056)	(0.027)	(0.056)	(0.027)
Risk	-0.342	-2.560***	-1.283	-2.543***	-0.402	-2.401***	-0.248	-0.302	-0.248	-0.303	-0.248	-0.263
	(0.352)	(0.109)	(2.677)	(0.110)	(0.682)	(0.091)	(0.575)	(1.258)	(0.575)	(1.259)	(0.575)	(1.282)
Bank Age	0.057**	0.092***	0.028	0.094***	0.025***	0.071***	0.030	0.013	0.030	0.013	0.030	0.011
	(0.016)	(0.016)	(0.098)	(0.017)	(0.008)	(0.013)	(0.180)	(0.154)	(0.180)	(0.154)	(0.180)	(0.155)
Conglomerate	0.425***	0.069*	0.359	0.009	0.488***	0.408***	0.721**	-0.801***	0.721**	-0.801***	0.721**	-0.804***
	(0.035)	(0.036)	(0.210)	(0.037)	(0.017)	(0.031)	(0.326)	(0.292)	(0.326)	(0.291)	(0.326)	(0.294)
Board Size	0.032**	-0.048**	-0.018	-0.050**	-0.152***	-0.381***	0.289	-0.410**	0.289	-0.410**	0.289	-0.412**
	(0.018)	(0.022)	(0.107)	(0.023)	(0.007)	(0.018)	(0.179)	(0.182)	(0.179)	(0.182)	(0.179)	(0.182)
Constant	-8.352***	1.496***	-5.310***	8.062***	-7.004***	1.666***	8.287***	-1.537	-6.227*	6.698***	8.722***	-1.344
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(1.457)	(4.667)	(2.037)	(1.544)	(1.442)
Sigma		-31.827***		-31.815***		-32.027***		-33.614***		-33.618***		-33.590***
		(0.005)		(0.005)		(0.005)		(1.016)		(1.017)		(1.020)
N	465	465	465	465	465	465	465	465	465	465	465	465
r2	0.861		0.861		0.861		0.275		0.275		0.275	
N_clust	93	93	93	93	93	93	93	93	93	93	93	93

This table presents the estimated results for the structure-performance relationship. All specifications include year and firm fixed effects. Standard error robust to heteroscedasticity and clustering at firm level are given in parentheses. Significance indicators: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.7: Market Structure and Performance - accounting measures

	NIM			ROE			ROA			CIR		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
HHI	0.301***			1.174***			1.463***			-0.658**		
	(0.019)			(0.141)			(0.170)			(0.265)		
HHI Dual		0.163***			0.637***			0.794***			-0.357**	
		(0.011)			(0.076)			(0.092)			(0.135)	
CR5			0.431***			1.684***			0.210***			-0.944**
			(0.128)			(0.220)			(0.024)			(0.493)
Bank Size	0.273**	0.275**	0.275**	0.808***	0.803***	0.808***	1.269***	1.264***	1.269***	0.542***	0.542***	0.541***
	(0.111)	(0.113)	(0.113)	(0.048)	(0.043)	(0.048)	(0.136)	(0.134)	(0.136)	(0.054)	(0.054)	(0.051)
Market Share	-0.191	-0.194	-0.191	0.228***	0.228***	0.226***	1.426***	1.425***	1.425***	0.389***	0.387***	0.389***
	(0.152)	(0.154)	(0.152)	(0.029)	(0.028)	(0.028)	(0.426)	(0.426)	(0.426)	(0.037)	(0.037)	(0.037)
Ownership	0.197***	0.172***	0.197***	-0.453	-0.453	-0.456	-0.625	-0.622	-0.620	0.254***	0.255***	0.251***
	(0.051)	(0.050)	(0.053)	(0.350)	(0.350)	(0.349)	(0.560)	(0.559)	(0.559)	(0.056)	(0.056)	(0.056)
OBS Activity	-0.277***	-0.277***	-0.277***	-0.295***	-0.292***	-0.294***	0.415	0.413	0.411	-0.339***	-0.337***	-0.339***
	(0.045)	(0.060)	(0.046)	(0.024)	(0.022)	(0.024)	(0.326)	(0.326)	(0.326)	(0.030)	(0.030)	(0.030)
Risk	-0.238***	-0.388***	-0.239***	-0.180	-0.179	-0.180	-0.248	-0.248	-0.248	-0.589	-0.588	-0.589
	(0.068)	(0.083)	(0.068)	(0.137)	(0.136)	(0.137)	(0.158)	(0.158)	(0.158)	(0.551)	(0.551)	(0.551)
Bank Age	-0.035***	-0.034***	-0.035***	-0.234***	-0.233***	-0.234***	0.063***	0.063***	0.063***	-0.315***	-0.314***	-0.315***
	(0.015)	(0.013)	(0.015)	(0.022)	(0.022)	(0.022)	(0.005)	(0.005)	(0.005)	(0.023)	(0.023)	(0.023)
Conglomerate	0.153***	0.156***	0.153***	-0.202	-0.205	-0.202	-0.154	-0.155	-0.157	-0.356***	-0.355***	-0.357***
	(0.044)	(0.049)	(0.044)	(0.225)	(0.227)	(0.225)	(0.225)	(0.227)	(0.227)	(0.033)	(0.033)	(0.033)
Board Size	0.581***	0.582***	0.582***	0.363***	0.364***	0.363***	0.174***	0.174***	0.171***	-0.253***	-0.253***	-0.251***
	(0.186)	(0.189)	(0.189)	(0.049)	(0.050)	(0.049)	(0.015)	(0.015)	(0.014)	(0.045)	(0.045)	(0.041)
Constant	0.587***	0.471	0.591***	-1.319	-4.695	0.557	-0.504	-0.619	-0.333	0.208	0.464	0.200
	(0.184)	(0.856)	(0.174)	(0.254)	(0.547)	(0.300)	(0.699)	(0.671)	(0.713)	(0.192)	(0.444)	(0.185)
N	465	465	465	465	465	465	465	465	465	465	465	465
r2	0.290	0.290	0.290	0.358	0.358	0.358	0.875	0.875	0.875	0.675	0.675	0.675
N_clust	93	93	93	93	93	93	93	93	93	93	93	93

This table presents the estimated results structure-performance relationship using alternate performance measures. All specifications include year and firm fixed effects. Standard error robust to heteroscedasticity and clustering at firm level are given in parentheses. Significance indicators: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.4.4. Market structure, bank conduct and performance

This section addresses the second and fourth assumptions of the SCP paradigm. The market structure effect on bank performance must decrease in magnitude (partial mediation) or becomes insignificant (perfect mediation) upon the incorporation of the bank conduct indicator into the model. In addition, bank conduct must significantly affect performance in all cases. Table 3.8 reports the estimation results of Eqn. (3.3) with performance captured via the bank efficiency[14] score and rank, and bank conduct captured via the PRH statistic (total revenue). The results show that the coefficients on the market structure indicators remain significantly positive (score) or negative (rank), whilst the bank conduct variable is also positive (rank) or negative (score) and significant in all model specifications. Nevertheless, the magnitude of the coefficients on the market structure indicators has declined in all model specifications, therefore, implying that the behaviour or conduct of banks partially mediates the market structure-performance nexus.

Furthermore, Table 3.9 reports the results where bank conduct is captured via the PCM (based on the adjusted Lerner). Indeed, the results in this section confirm and complement the main findings that bank behaviour or conduct partially mediates the market structure-performance nexus. The coefficient on the bank conduct variable is positive (score) or negative (rank) and significant in all model specifications. Also, the magnitude of the coefficients on the market structure indicators has declined in all model specifications, hence providing confirmation that bank conduct partially mediates the relationship between interbank market structure and bank performance. These findings confirm the position of prior studies (e.g., Mirzaei et al., 2013; Homma et al., 2014) that market structure (i.e., degree of concentration) influences bank conduct or behaviour via collusive and/or monopolistic pricing, to consequently increase bank performance. Monticini and Ravazzolo (2014) show that interbank market frictions that resulted from the liquidity crises increased bank's ability to charge higher intraday interest rate spreads and thus, created a platform for abnormal gains through arbitrage. Overall, I show that by engaging in interbank operations, banks can change their behaviour to ultimately influence their performance goals. However, while it may be individually advantageous for banks to collude or monopolise financial networks for abnormal gains, the resulting

[14] I also performed the analysis with accounting performance indicators (i.e., NIM, ROE, ROA and CIR). The findings from these estimations are similar to those found using the efficiency measures.

global network structure may be exposed to greater systemic risks. So far, the estimation results have buttressed all the conditions necessary for the validity of the SCP hypothesis.

Table 3.8: Market Structure, Conduct and Performance

	PE SCORE	PE RANK	PE SCORE	PE RANK	PE SCORE	PE RANK	CE SCORE	CE RANK	CE SCORE	CE RANK	CE SCORE	CE RANK
HHI	0.025***	-0.020***					0.271***	-0.152***				
	(0.000)	(0.000)					(0.000)	(0.000)				
HHI Dual			0.131***	-0.106***					0.142***	-0.030***		
			(0.000)	(0.000)					(0.000)	(0.000)		
CR5					0.037***	-0.036***					0.406***	-0.242***
					(0.000)	(0.000)					(0.095)	(0.029)
PRH	-0.334***	0.781***	-0.337***	0.804***	-0.329***	0.722***	-0.378**	0.803***	-0.412**	0.830***	-0.333**	0.730***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.156)	(0.123)	(0.161)	(0.126)	(0.149)	(0.115)
Bank Size	0.002	-0.017	0.001	-0.016	0.002	-0.016	-0.421***	0.313***	-0.421***	0.313***	-0.421***	0.313***
	(0.003)	(0.014)	(0.007)	(0.014)	(0.002)	(0.010)	(0.111)	(0.099)	(0.111)	(0.099)	(0.111)	(0.099)
Market Share	0.030	0.811	0.072	0.793	0.039	0.727	0.704	-0.294	0.704	-0.296	0.704	-0.304
	(0.151)	(0.859)	(0.131)	(0.848)	(0.131)	(0.643)	(0.740)	(0.526)	(0.740)	(0.527)	(0.740)	(0.526)
Ownership	-0.017***	-0.006	-0.011	-0.007	-0.013***	-0.003	0.798**	-0.381	0.798**	-0.381	0.798**	-0.380
	(0.005)	(0.012)	(0.016)	(0.012)	(0.004)	(0.009)	(0.322)	(0.279)	(0.322)	(0.279)	(0.322)	(0.279)
OBS Activity	-0.002**	-0.003	0.001	-0.003	-0.002**	-0.001	0.160***	-0.079***	0.160***	-0.079***	0.160***	-0.079***
	(0.001)	(0.005)	(0.002)	(0.005)	(0.001)	(0.004)	(0.056)	(0.029)	(0.056)	(0.029)	(0.056)	(0.029)
Risk	-0.047	-2.142***	-0.274	-2.141***	-0.079	-1.934***	-0.248	1.366**	-0.248	1.368**	-0.248	1.392**
	(0.046)	(0.161)	(0.334)	(0.063)	(0.074)	(0.355)	(0.575)	(0.687)	(0.575)	(0.687)	(0.575)	(0.687)
Bank Age	0.012***	0.039***	-0.008	0.038***	0.013***	0.027***	0.030	0.057	0.030	0.057	0.030	0.055
	(0.004)	(0.009)	(0.009)	(0.008)	(0.002)	(0.006)	(0.180)	(0.171)	(0.180)	(0.171)	(0.180)	(0.171)
Conglomerate	0.006	-0.029	-0.004	-0.029	0.005	-0.028	0.721**	-0.663**	0.721**	-0.663**	0.721**	-0.663**
	(0.007)	(0.023)	(0.019)	(0.023)	(0.004)	(0.018)	(0.326)	(0.323)	(0.326)	(0.323)	(0.326)	(0.323)
Board Size	-0.005	-0.009	0.004	-0.008	-0.006**	-0.004	0.289	-0.488***	0.289	-0.488***	0.289	-0.487***
	(0.004)	(0.011)	(0.009)	(0.011)	(0.003)	(0.008)	(0.179)	(0.158)	(0.179)	(0.158)	(0.179)	(0.158)
Constant	-7.733***	1.596***	-1.007***	9.116***	-5.613***	1.616***	9.148***	-1.430	-9.500***	7.777***	9.379***	-1.351
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(1.457)	(3.077)	(2.212)	(1.146)	(1.441)
Sigma		-32.743***		-32.521***		-33.509***		-32.316***		-32.315***		-32.318***
		(0.009)		(0.013)		(0.017)		(0.176)		(0.176)		(0.176)
N	465	465	465	465	465	465	465	465	465	465	465	465
r2	0.857		0.857		0.857		0.275		0.275		0.275	
N_clust	93	93	93	93	93	93	93	93	93	93	93	93

This table presents the estimated results for the structure-conduct-performance. All specifications include year and firm fixed effects. Standard error robust to heteroscedasticity and clustering at firm level are given in parentheses. Significance indicators: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.9: Market Structure, Conduct and Performance – PCM2 (Lerner)

	PE SCORE	PE RANK	PE SCORE	PE RANK	PE SCORE	PE RANK	CE SCORE	CE RANK	CE SCORE	CE RANK	CE SCORE	CE RANK
HHI	0.115***	-0.161***					0.169	-0.088				
	(0.001)	(0.002)					(0.192)	(0.083)				
HHI Dual			0.425***	-0.514***					0.092	-0.043		
			(0.060)	(0.061)					(0.104)	(0.042)		
CR5					0.165***	-0.315***					0.242	-0.186
					(0.004)	(0.019)					(0.276)	(0.149)
PCM2	0.676***	-0.231**	-0.627***	-0.235**	0.607***	-0.184**	0.950***	-0.726***	0.950***	-0.728***	0.950***	-0.707***
	(0.041)	(0.117)	(0.048)	(0.119)	(0.010)	(0.098)	(0.066)	(0.050)	(0.066)	(0.050)	(0.066)	(0.050)
Bank Size	0.008	-0.017	0.010	-0.017	0.011	-0.013	-0.410***	0.305***	-0.410***	0.305***	-0.410***	0.306***
	(0.015)	(0.031)	(0.102)	(0.031)	(0.009)	(0.026)	(0.111)	(0.099)	(0.111)	(0.099)	(0.111)	(0.099)
Market Share	0.414	0.384	0.168	0.208	0.179	0.207	0.690	-2.719	0.690	-2.723	0.690	-2.718
	(1.047)	(1.102)	(6.826)	(1.108)	(0.495)	(0.977)	(0.732)	(4.195)	(0.733)	(4.194)	(0.732)	(4.202)
Ownership	-0.012	-0.014	-0.023	-0.015	-0.000	-0.012	0.792**	-0.435*	0.792**	-0.435*	0.792**	-0.434*
	(0.050)	(0.048)	(0.321)	(0.049)	(0.025)	(0.038)	(0.318)	(0.258)	(0.318)	(0.258)	(0.318)	(0.258)
OBS Activity	-0.002	-0.014	-0.008	-0.014	-0.006*	-0.011	0.160***	-0.083***	0.160***	-0.083***	0.160***	-0.083***
	(0.005)	(0.010)	(0.029)	(0.010)	(0.003)	(0.009)	(0.056)	(0.027)	(0.056)	(0.027)	(0.056)	(0.027)
Risk	-0.298	-2.457***	-1.279	-2.441***	-0.407	-2.336***	-0.197	-0.151	-0.197	-0.150	-0.197	-0.133
	(0.523)	(0.164)	(3.337)	(0.166)	(0.516)	(0.132)	(0.565)	(0.138)	(0.565)	(0.139)	(0.565)	(0.139)
Bank Age	0.003	0.091***	0.030	0.093***	0.025*	0.072***	0.027	0.014	0.027	0.014	0.027	0.013
	(0.025)	(0.031)	(0.165)	(0.032)	(0.013)	(0.025)	(0.177)	(0.156)	(0.177)	(0.156)	(0.177)	(0.156)
Conglomerate	0.037	0.023	0.038	0.025	0.046	0.017	0.714**	-0.778***	0.714**	-0.777***	0.714**	-0.780***
	(0.048)	(0.052)	(0.354)	(0.053)	(0.029)	(0.043)	(0.319)	(0.294)	(0.319)	(0.294)	(0.319)	(0.296)
Board Size	0.017	-0.087**	-0.021	-0.089**	-0.011	-0.070**	0.307*	-0.427**	0.307*	-0.427**	0.307*	-0.428**
	(0.029)	(0.037)	(0.179)	(0.038)	(0.016)	(0.031)	(0.177)	(0.191)	(0.177)	(0.192)	(0.177)	(0.191)
Constant	-8.352***	1.366***	-5.310***	7.116***	-7.004***	1.546***	9.737***	-1.031	3.173	1.991	9.939***	-0.876
	(0.106)	(0.082)	(0.545)	(0.506)	(0.228)	(0.076)	(1.991)	(1.191)	(9.009)	(3.353)	(1.841)	(1.191)
Sigma		-31.922***		-31.913***		-32.099***		-33.531***		-33.532***		-33.517***
		(0.062)		(0.064)		(0.050)		(1.089)		(1.091)		(1.087)
N	465	465	465	465	465	465	465	465	465	465	465	465
r2	0.918		0.918		0.918		0.282		0.282		0.282	
N_clust	93		93		93	93	93	93	93	93	93	93

This table presents the estimated results for the structure-conduct-performance using alternate conduct measures. All specifications include year and firm fixed effects. Standard error robust to heteroscedasticity and clustering at firm level are given in parentheses. Significance indicators: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.4.5. Robustness tests: mediation analysis with bootstrapped confidence intervals

In this section, I perform a few more tests to provide further validation of the indirect relationship between interbank market structure and bank performance. In other words, from interbank market structure to bank conduct, and subsequently from bank conduct to bank performance. I follow the approach of prior studies (e.g., Khan et al., 2017) and calculate the Sobel, Aroian and Goodman test scores (z-value) to confirm the significance/insignificance of the indirect (mediated) effect. The coefficients of interbank market structure based on Eqn. (3.1) (Table 3.5) and bank conduct based on Eqn. (3.2) (Table 3.7/3.8) are utilised to calculate the Sobel, Aroian and Goodman test statistic (z). First, a comparison of the coefficients on the market structure indicators in the first and second row of Table 3.10 distinctly shows that introduction of bank conduct into the model reduces the market structure effect on bank performance. Furthermore, regardless of whether bank conduct is measured via the PRH (total revenue) or the PCM (adjusted Lerner), the statistic (z) under the Sobel, Aroian and Goodman test are significant (at the 1% level) in all specifications. Thus, the null hypothesis specifying the absence of any indirect relationship between interbank market structure and bank performance is rejected to confirm the presence of a mediation effect in the structure–performance nexus. Nevertheless, the effect of the market structure on the bank performance remains significant, thus pointing towards a partially mediated effect.

Although the above test results may be acceptable, they can be biased (Preacher and Hayes, 2004; Fritz et al., 2012). Thus, I proceed to estimate the asymmetric confidence intervals for the mediated effect. The bootstrapped estimates of the indirect effect, with 5,000 replications, are similar to the point estimate estimated via the conventional regression tests, and the true indirect effect estimated for the percentile, bias-corrected, and bias-corrected and accelerated confidence intervals ranges between -0.855 and 0.788 with 95% confidence. Given that none of the estimated 95% confidence interval is zero, I can infer that the indirect effect is significantly different from zero. Hence, the conclusion that bank conduct partially mediates the relationship between interbank market structure and bank performance.

Taken together, these results confirm that the SCP hypothesis provides a valid explanation for the positive nexus between interbank market structure and bank performance among UK banks. Nevertheless, the SCP may not adequately explain the structure-performance nexus due to the presence of a partially mediated channel through bank conduct. A probable explanation for this outcome may include product differentiation and where strategic spillovers between two distinct markets can generate an inefficient allocation of resources and consequently stimulate collusion and/or monopolistic pricing. Key policy implications are that banks (especially larger banks) can earn abnormal profits partially through anticompetitive behaviour when the interbank market is highly concentrated to stimulate collusion and monopolistic pricing. Accordingly, consolidation activities of banks must be effectively monitored/scrutinized to prevent banks from holding/controlling substantial resources that enables them to create/possess extensive market power.

Table 3.10: Mediation Analysis for SCP

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Structure–Performance (without conduct) (Table 3.6)	0.115***	-0.183***	0.624***	-0.930***	0.165***	-0.348***	0.372***	0.232***	0.202***	-0.117***	0.535***	-0.312**
	(0.000)	(0.000)	(0.004)	(0.004)	(0.003)	(0.001)	(0.041)	(0.021)	(0.000)	(0.000)	(0.138)	(0.142)
Structure–Performance (with conduct) (Table 3.8/9)	0.025***	-0.020***	0.131***	-0.106***	0.037***	-0.036***	0.169	-0.088	0.092	-0.043	0.242	-0.186
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.192)	(0.083)	(0.104)	(0.042)	(0.276)	(0.149)
Coefficient on Conduct (in S–C–P model) (Table 3.8/9	-0.334***	0.781***	-0.337***	0.804***	-0.329***	0.722***	0.950***	-0.726***	0.950***	-0.728***	0.950***	-0.707***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.066)	(0.050)	(0.066)	(0.050)	(0.066)	(0.050)
Structure–Conduct (Table 3.5)	-0.270***	-0.270***	-0.147***	-0.147***	-0.388***	-0.388***	0.215***	0.215***	0.117***	0.117***	0.308***	0.308***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Complementary tests												
Sobel test	-0.353***	0.781***	-0.337***	0.804***	-0.349***	0.722***	1.043***	-0.710***	1.046***	-0.711***	1.022***	-0.707***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.043)	(0.034)	(0.043)	(0.034)	(0.043)	(0.034)
Aroian test	-0.250***	-0.250***	-0.161***	-0.161***	-.388***	-0.388***	0.198***	0.198***	0.149***	0.149***	0.301***	0.301***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.006)	(0.006)	(0.017)	(0.017)	(0.009)	(0.009)	(0.006)	(0.006)
Goodman test	-8.824***	1.955***	-5.685***	1.293***	-.079***	-0.843***	1.021***	1.080***	5.142***	5.449***	0.184**	0.193***
	(0.004)	(0.088)	(0.021)	(0.047)	(0.637)	(0.013)	(0.046)	(0.381)	(0.229)	(0.193)	(0.083)	(0.068)
Bootstrapped tests												
Indirect Effect	-8.824***	1.955***	-5.685***	1.293***	-4.079***	-0.843***	1.021***	1.080***	5.142***	5.449***	0.184**	0.192***
	(0.004)	(0.088)	(0.021)	(0.047)	(0.637)	(0.013)	(0.046)	(0.386)	(0.232)	(0.195)	(0.083)	(0.069)
Percentile CI (95%) - Lower	-0.129	0.120	-0.791	0.088	-0.107	-0.052	0.035	-0.440	0.017	-0.203	0.062	-0.855
Upper	-0.054	0.283	-0.304	0.178	0.264	0.213	0.401	-0.036	0.189	-0.018	0.788	-0.060
Bias-corrected CI (95%) - Lower	-0.126	0.117	-0.772	0.086	-0.103	-0.059	0.032	-0.410	0.016	-0.189	0.057	-0.777
Upper	-0.050	0.281	-0.372	0.177	0.310	0.206	0.367	-0.034	0.172	-0.017	0.734	-0.055
Bias-corrected and accelerated CI (95%) - Lower	-0.126	0.116	-0.770	0.086	-0.104	-0.058	0.021	-0.289	0.010	-0.143	0.041	-0.543
Upper	-0.050	0.280	-0.370	0.176	0.306	0.207	0.283	-0.022	0.136	-0.012	0.514	-0.033

This table presents the mediation analysis based on the SAG and the Bootstrapped tests. Models 1, 3, & 5 (2, 4, & 6) are estimated using the PE SCORE (PE RANK) as performance measures and Conduct captured via the PRH. Models 7, 9, & 11 (8, 10, & 12) are estimated using the CE SCORE (CE RANK) as performance measures and Conduct captured via the PCM2. Market structure is captured via the HHI, HHI Dual and CR5 under Models 1 & 2 (5 & 6); 3 & 4 (7 & 8); and 5 & 6 (11 & 12) respectively. Model specifications include all other control variables, year and firm fixed effects. Significance indicators: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.4.6. Market structure, bank conduct and performance: domestic vs. foreign owned banks

In this section, I examine whether bank ownership structure (foreign vs. domestic) matters for the validity of the SCP hypothesis. I focus on bank ownership for four reasons. First, UK has the most competitive financial centre worldwide (Global Financial Centres Index - GFCI 23, 2018). The UK banking system is notable for the greater concentration of banking system assets among a few banks with global operations, and the ability of foreign banks to match the large-scale operations and size of domestic banks (Hills et al., 2019). As such, foreign subsidiaries and foreign branches have a large presence and accounts for substantial financial linkages in terms of bank lending and/or funding. Second, the transfer of capital across borders makes interbank activities of foreign banks distinct from those of domestic banks (De Haas and Van Lelyveld, 2010). Foreign banks have highly stable funding sources and lending patterns that enables them to enjoy interbank market power. Foreign banks also hold a geographically differentiated credit portfolio that enable them to mitigate any adverse crisis effects in domestic financial markets (Allen et al., 2018). Third, the interbank market decisions of foreign subsidiaries may be significantly determined by the current policy of the multinational bank rather than by host country institutional factors (Allen et al., 2013). However, the current home country's economic conditions strongly affect foreign bank operations (Adams-Kane et al., 2017). More importantly, countries that hosts more foreign banks have a very significant portion of their interbank market assets controlled by foreign banks. Fourth, prior empirical studies (e.g., Edison et al. 2002; Lensink and Hermes 2004; Kouretas and Tsoumas 2016) stress that foreign banks are more innovative, better managed, and have better risk management procedures. Therefore, foreign bank presence should enhance financial stability, and stimulate a spillover of new/innovative ideas and expertise to improve the performance of domestic banks rather than disrupting financial stability via increased risk-taking behaviour/conduct of domestic banks (Sengupta 2007; Ukaegbu and Oino 2014). However, the existing literature gives very limited results on the interactive role of interbank market structure (concentration/competition), conduct and performance. Thus, this section focuses on empirically examining the effects of foreign bank penetration on the SCP hypothesis. (concentration/competition) and foreign bank presence on bank conduct/behaviour and ultimately performance.

I split the sample of banks based on ownership (foreign owned vs. domestically owned) using the Global Ultimate Owner[15] (GUO) indicator from Orbis, complemented with publicly available information from the Bank of England and related institutions. I classify banks as foreign owned if the country code of the global ultimate owner at the highest consolidation level is not 'GB' where the bank operates (Agrawal et al., 2017). The estimation results and subsequent mediation tests are reported in Table 3.11 and 3.12. The first and second rows show the estimated results based on Eqns. (3.2) and (3.3) where the dependent variable is performance based on PE (Model 1-6) and CE (Model 1-6), and the structure variable is HHI (Models 1, 2, 5 & 6), HHI Dual (3, 4, 7 & 8); and CR5 (5, 6, 11 & 12) respectively. The third row shows the coefficients on bank conduct from Eqn. (3.3) where the conduct variable is the PRH (based on total revenue). The fourth row shows the estimated results based on Eqn. (3.1) where the dependent variable is the PRH (based on total revenue) and the structure variable is the HHI, HHI Dual and CR5 under Models 1 & 2 (5 & 6); 3 & 4 (7 & 8); and 5 & 6 (11 & 12) respectively. All model specifications include control variables, firm fixed effects and time dummies.

First, the results in this section are consistent with, and complementary to the main findings that interbank market structure impacts significantly on bank conduct and performance. However, it is worth noting that the magnitude of the impact and significance on the bank conduct coefficient is greater for foreign banks. The implication of this is that foreign bank participation in the interbank market is a key dimension of bank conduct and competition (Claessens and Laeven, 2004). Foreign banks behave more anti-competitively under higher interbank market concentration and thus, are more likely to refuse credit to small or opaque organizations (Beck et al., 2018). Although bank performance is significantly positive (efficiency score) or negative (efficiency rank) in the structure-performance estimation, the magnitude of the coefficients indicates that market structure matters most for foreign banks' profit efficiency but for domestic banks' cost efficiency. For the key SCP validity test, I observe a reduction in the market structure coefficients when bank conduct is incorporated into the model. However, it is worth noting that, while the market structure coefficients for both foreign and domestic banks remained significant under profit efficiency, they are insignificant under cost efficiency

[15] An individual or entity is classified as a GUO if they control at least 50.01% of the entity (Claessens and Van Horen, 2013, 2014).

for foreign banks. The implication of this result is that, while bank conduct partially mediates the structure-performance relationship in terms of profits, bank conduct fully mediates the structure-performance relationship in terms of costs, particularly for foreign banks. Hence, the interbank market structure is cost efficient for foreign banks, and thus encourages greater participation of foreign banks in financial networks.

Further analysis via the Sobel, Aroian and Goodman test statistics as well as the bootstrapped estimates of the indirect effect indicates that the mediation effect of bank conduct is robust for all samples. A probable explanation for these results is that foreign banks characterised by their large resource pool and good international reputation will collude with their domestic peers by acting as correspondent banks in order to overcome asymmetric information problems (Freixas and Holthausen, 2004). These findings are consistent with prior studies (e.g., Williams, 2012; Gormley, 2010; Claessens and Van Horen 2012, 2014, 2015) that bank ownership structure matters for a bank's performance, operational efficiency and stability. Claessens and Van Horen (2012) argues that greater foreign bank presence decreases profitability but increases overhead costs for domestic banks. Gormley (2010) reported a market-wide upsurge in bank loans of domestic banks due to foreign bank presence. Hence, the conclusion that the extent and nature of the foreign bank entry affects the risk-taking behaviour or conduct of domestic banks. However, these studies failed to establish any link between market structure (concentration/competition), conduct and performance.

Taken together, the results suggest that bank ownership structure matters for the validity of the SCP hypothesis. The cross-border transfer of bank capital raises the degree of skepticism about the essential role of foreign banks; especially the belief that greater foreign presence enhances profitability and financial stability of the domestic banking market. Both domestic and foreign banks engage in anticompetitive behaviour when the interbank market is highly concentrated via collusion and monopolistic pricing and thus, they will rely on their higher solvency to offer lower interbank rates. Although a large proportion of foreign banks' activities may be located outside the host market, an increase in interbank concentration that reflects a decrease in competition do affect foreign bank's performance and particularly conduct. Therefore, the host country's market conditions strongly affect foreign bank operations and profitability as foreign banks will adjust their lending and deposit rates in response to changes in the host market's economic conditions

(Claessens and Van Horen, 2013; Adams-Kane et al., 2017). In order to derive policy implications, it is therefore crucial for policymakers to better understand the gains of financial globalization, and ensure the implementation of strategic policies that will maximize the rewards from the opening of their banking sector (Wu et al., 2017).

Table 3.11: Mediation Analysis for SCP - Domestic Banks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Structure–Performance (without conduct)	0.175***	-0.178***	0.235***	-0.902***	0.133***	-0.348***	0.483***	-0.248***	0.472***	-0.729***	0.414***	-0.496***
	(0.031)	(0.000)	(0.017)	(0.000)	(0.041)	(0.008)	(0.077)	(0.010)	(0.039)	(0.052)	(0.131)	(0.140)
Structure–Performance (with conduct)	0.107***	-0.021***	0.053***	-0.111***	0.029***	-0.037***	0.128***	-0.158*	0.258***	-0.331*	0.236*	-0.320**
	(0.007)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.042)	(0.093)	(0.030)	(0.253)	(0.131)	(0.155)
Coefficient on Conduct (in S–C–P model)	-0.348***	0.722***	-0.349***	0.776***	-0.346***	0.702***	-0.839***	0.808***	-0.852***	0.927***	-0.808***	0.862***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.033)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Structure–Conduct	-0.036***	-0.036***	-0.022***	-0.022***	-0.277**	-0.277**	-0.036***	-0.036***	-0.022***	-0.022***	-0.277**	-0.277**
	(0.008)	(0.008)	(0.005)	(0.005)	(0.119)	(0.119)	(0.008)	(0.008)	(0.005)	(0.005)	(0.119)	(0.119)
Complementary tests												
Sobel test	-0.348***	0.753***	-0.349***	0.776***	-0.346***	0.702***	-0.839***	0.808***	-0.852***	0.927***	-0.808***	0.862***
	(0.003)	(0.009)	(0.001)	(0.009)	(0.001)	(0.008)	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)	(0.010)
Aroian test	0.036***	0.036***	0.022***	0.022***	0.277**	0.277**	0.036***	0.036***	0.022***	0.022***	0.277**	0.277**
	(0.003)	(0.008)	(0.005)	(0.005)	(0.119)	(0.119)	(0.008)	(0.008)	(0.005)	(0.005)	(0.119)	(0.119)
Goodman test	-1.248***	-2.698***	-0.763***	-1.696***	-0.959***	-0.194***	3.005**	3.253**	-1.861***	2.025***	0.224***	0.239***
	(0.098)	(0.022)	(0.005)	(0.114)	(0.016)	(0.003)	(1.399)	(1.430)	(0.232)	(0.250)	(0.004)	(0.005)
Bootstrapped tests												
Indirect Effect	-1.248***	-2.698***	-0.763***	-1.696***	-0.959***	-0.194***	3.005**	3.253**	-1.861***	2.025***	0.224***	0.239***
	(0.099)	(0.022)	(0.005)	(0.115)	(0.016)	(0.003)	(1.473)	(1.509)	(0.266)	(0.287)	(0.006)	(0.006)
Percentile CI (95%) - Lower	-0.268	0.052	-0.151	0.055	-0.289	-0.209	-0.123	-0.457	-0.757	-0.262	-0.135	0.054
Upper	-0.024	0.594	-0.023	0.344	0.088	0.582	0.044	0.126	0.240	0.725	0.049	0.130
Bias-corrected CI (95%) - Lower	-0.271	0.063	-0.157	0.067	-0.277	-0.193	-0.148	-0.299	-0.859	-0.199	-0.179	0.028
Upper	-0.025	0.626	-0.025	0.373	0.099	0.603	0.031	0.158	0.173	0.833	0.026	0.171
Bias-corrected and accelerated CI (95%) - Lower	-0.262	0.054	-0.154	0.061	-0.277	-0.197	-0.150	-0.315	-0.895	-0.204	-0.179	0.031
Upper	-0.022	0.599	-0.024	0.364	0.098	0.603	0.029	0.150	0.162	0.809	0.026	0.166

This table presents the mediation analysis based on the SAG and the Bootstrapped tests. Models 1, 3, & 5 (2, 4, & 6) are estimated using the PE SCORE (PE RANK) as performance measures and Conduct captured via the PRH. Models 7, 9, & 11 (8, 10, & 12) are estimated using the CE SCORE (CE RANK) as performance measures. Market structure is captured via the HHI, HHI Dual and CR5 under Models 1 & 2 (5 & 6); 3 & 4 (7 & 8); and 5 & 6 (11 & 12) respectively. Model specifications include all other control variables, year and firm fixed effects. Significance indicators: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.12: Mediation Analysis for SCP – Foreign Banks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Structure–Performance (without conduct)	0.625**	-0.733***	0.495**	-0.866***	0.977***	-0.352***	0.126***	-0.158***	0.631***	-0.781***	0.495***	-0.451**
	(0.304)	(0.106)	(0.167)	(0.026)	(0.034)	(0.005)	(0.025)	(0.028)	(0.023)	(0.082)	(0.047)	(0.262)
Structure–Performance (with conduct)	0.105***	-0.212***	0.051***	-0.109***	0.233***	-0.237***	0.065	-0.097	0.473	-0.403	0.326	-0.379
	(0.005)	(0.000)	(0.000)	(0.000)	(0.005)	(0.000)	(0.046)	(0.117)	(0.414)	(0.850)	(0.441)	(0.288)
Coefficient on Conduct (in S–C–P model)	-0.350***	0.729***	-0.351***	0.769***	-0.348***	0.711***	-0.824***	0.828***	-0.845***	0.850***	-0.787***	0.782***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.004)	(0.003)	(0.005)	(0.003)	(0.000)	(0.000)
Structure–Conduct	-0.048***	-0.048***	-0.029***	-0.029***	-0.389***	-0.389***	-0.048***	-0.048***	-0.029***	-0.029***	-0.389***	-0.389***
	(0.008)	(0.008)	(0.004)	(0.004)	(0.098)	(0.098)	(0.008)	(0.008)	(0.004)	(0.004)	(0.098)	(0.098)
Complementary tests												
Sobel test	-0.350***	0.764***	-0.351***	0.788***	-0.348***	0.711***	0.824***	0.828***	-0.845***	0.850***	-0.787***	0.782***
	(0.001)	(0.006)	(0.001)	(0.006)	(0.001)	(0.005)	(0.012)	(0.077)	(0.012)	(0.077)	(0.012)	(0.077)
Aroian test	0.048***	0.048***	0.029***	0.029***	0.389***	0.389***	0.048***	0.048***	0.029***	0.029***	0.389***	0.389***
	(0.008)	(0.008)	(0.004)	(0.004)	(0.036)	(0.036)	(0.002)	(0.002)	(0.001)	(0.001)	(0.036)	(0.036)
Goodman test	-1.674***	3.656***	-1.006***	2.261***	-1.356**	-0.277***	0.394**	0.396***	-0.242***	0.244***	0.306***	0.304***
	(0.077)	(0.172)	(0.039)	(0.091)	(0.126)	(0.026)	(0.160)	(0.041)	(0.036)	(0.024)	(0.054)	(0.041)
Bootstrapped test												
Indirect Effect	-1.674***	3.656***	-1.006***	2.261***	-1.356***	-0.277***	0.394***	0.396***	-0.242***	0.244***	0.306***	0.304***
	(0.077)	(0.173)	(0.039)	(0.091)	(0.126)	(0.026)	(0.066)	(0.044)	(0.038)	(0.026)	(0.069)	(0.049)
Percentile CI (95%) - Lower	-0.292	0.198	-0.168	0.133	-0.301	0.005	-0.192	-0.370	-0.107	-0.218	-0.166	-0.035
Upper	-0.088	0.659	-0.060	0.381	-0.004	0.597	0.086	0.014	0.507	0.773	0.075	0.126
Bias-corrected CI (95%) - Lower	-0.283	0.190	-0.163	0.131	-0.285	-0.026	-0.194	-0.317	0.108	-0.199	-0.200	-0.023
Upper	-0.084	0.632	-0.057	0.379	0.007	0.561	0.083	0.014	0.502	0.794	0.059	0.148
Bias-corrected and accelerated CI (95%) - Lower	-0.274	0.182	-0.160	0.127	-0.283	-0.029	-0.195	-0.324	0.109	-0.206	-0.200	-0.024
Upper	-0.082	0.614	-0.055	0.372	0.007	0.557	0.082	0.014	0.496	0.791	0.055	0.146

This table presents the mediation analysis based on the SAG and the Bootstrapped tests. Models 1, 3, & 5 (2, 4, & 6) are estimated using the PE SCORE (PE RANK) as performance measures and Conduct captured via the PRH. Models 7, 9, & 11 (8, 10, & 12) are estimated using the CE SCORE (CE RANK) as performance measures. Market structure is captured via the HHI, HHI Dual and CR5 under Models 1 & 2 (5 & 6); 3 & 4 (7 & 8); and 5 & 6 (11 & 12) respectively. Model specifications include all other control variables, year and firm fixed effects. Significance indicators: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.4.7. Market structure, bank conduct and performance: conglomerate vs non-conglomerate banks

The past decades have envisaged a rapid consolidation of banks worldwide, with UK banks becoming part of huge globalised conglomerates, and thus increasing concerns amongst policymakers about bank concentration (Shabani et al., 2015). International financial institutions operate in foreign jurisdictions via local conglomerates and cross-border lending. They create opportunities to improve financial and economic growth due to their vast capital, proficiency, liquidity and new/innovative technologies that consequently boost domestic competition and distribution of resources (Fischer, 2015). While consolidation is argued to promote/enhance efficiency and scale economy, the consolidation process and the resultant financial conglomerates may disrupt stability (Chronopoulos et al., 2011). Indeed, almost all the large, international financial institutions are to some extent financial conglomerates whose size and complexity might subvert effective regulation and supervision by both markets and authorities. For instance, their size and central role across the financial systems may grant them too much power: a situation identified as 'too-big or too-important-to-fail'. Moreover, the existence of internal capital markets within conglomerates ensures that parent banks can bail-out or recapitalise affiliated banks that would otherwise fail via a redistribution of capital resources amongst subsidiaries (Mistrulli, 2011). Therefore, what are the effects of the bank consolidation process on the SCP hypothesis? Although, ostensibly contrasting trends, consolidation may not necessarily suggest low interbank market concentration, given that consolidation may occur across different business lines or markets, or create fewer but very competitive parties (Berger et al., 2010). Nevertheless, both competition and consolidation may weaken the resilience of the interbank market as they increase interdependence/collusion amongst banks. This section therefore examines whether financial conglomeration matters for the validity of the SCP hypothesis.

I split the sample of banks based on whether the bank is affiliated with a conglomerate or not. The estimation results and subsequent mediation tests are reported in Table 3.13 and 3.14. First, the results in this section are consistent with and complementary to the main findings that interbank market structure impacts significantly on bank conduct and performance. The magnitude of the impact on the bank conduct coefficient is, however, slightly greater for non-conglomerate banks. This implies that interbank market participation is a key dimension of bank conduct and competition. Both conglomerate and non-conglomerate banks behave more anti-competitively under higher interbank market concentration though the slightly higher non-conglomerate conduct coefficient indicates that the core criteria for interbank participation are that the bank establishes itself as creditworthy and unconstrained by domestic regulations, yet ready to lend credit to small or opaque organizations. Although bank performance is significantly positive (score) or negative (rank) in the structure-performance estimation, the magnitude of the coefficients indicates that market structure matters for both conglomerate and non-conglomerate banks in terms of profit efficiency. In terms of cost efficiency, market structure matters particularly for conglomerate banks. In the SCP model, I observe a reduction in the market structure coefficients when bank conduct is incorporated into the estimation. However, it is worth noting that while the market structure coefficients on both profit and cost efficiency remained significant for conglomerate banks, they are insignificant for non-conglomerate banks. The implication of this result is that while bank conduct partially mediates the structure-performance relationship for conglomerate banks, bank conduct fully mediates the structure-performance relationship for non-conglomerate banks. Hence, the interbank market structure is both profit and cost efficient for non-conglomerate banks, and thus encourages greater participation of non-conglomerate banks in financial networks. For non-conglomerates, the contractual and informational framework plays a vital role in interacting with the interbank market structure and competition. Therefore, for non-conglomerates, credit information sharing will boost their access to credit and also enhance their credit decision-making (Brown et al., 2009).

Further analysis using the Sobel, Aroian and Goodman tests as well as the bootstrapped estimates of the indirect effect indicate that the mediation effect of bank conduct is robust for all samples. A probable explanation for these results is that, just like concentration, conglomeration also induces strong interdependence or collusive behaviour amongst affiliated banks. Apart from being related through financial interlinkages, affiliated banks will collude to mitigate shocks that hits one bank, given that these shocks will affect all banks of the same conglomerate (Mistrulli, 2011). Furthermore, bank consolidation and/or conglomeration happen both within business lines and also across business lines. For instance, the recent consolidation trend has led to financial conglomerates that combine at least two of the three formerly distinct functions of banks, securities firms or insurance companies. In this context, a conglomerate may have affiliates in both the financial and non-financial sector. As such, affiliated banks that are competitive in lending to the non-financial sector but lack the ability to generate funds can borrow funds from other affiliates that have with excess liquidity on the interbank market, and thus obtain the required funds to supply credit to the non-financial sector. Against this background, both banks would still be acting along their business lines that allow them to have a comparative advantage and thus, have increased credit portfolios and performance. These findings are consistent with prior studies that suggest that market microstructure and information flows have critical roles in modern financial systems (Carletti, 2010; Chronopoulos et al., 2011). For large and affiliated financial institutions, active market participation has undermined traditional activities based on pricing loans and deposits. The higher collusion of banks via direct linkages in the interbank markets or payment systems, or indirectly from the interdependency of their portfolios may create contagion effects (Allen et al., 2009).

Taken together, the results suggest that bank consolidation has important implications for the validity of the SCP hypothesis, and for policymakers. First, market structure, such as the number of banks or market share of the largest banks, may not be directly enforced through policy actions in market-based financial systems. Where there are seemingly opposing policy goals (e.g., deepening, broadening, and/or financial system stability), it is imperative to understand the trade-offs across these diverse goals regarding competition and collusion. Second, many regulatory policies that relate to banks' competitive behaviour have other, more direct, effects on bank stability than through their effects on competition (Carletti, 2010). Hence, given the range of regulatory policies available to policymakers, it is imperative to understand their effect on competition and stability, and also any differential impact on stability across different competitive environments. Third, a clear regulatory policy on how to address large systemic banks is essential. Although interventions and government support for such institutions may be inevitable during hard times, a vibrant and transparent framework on decision-making, responsibility and accountability for cost is necessary.

Table 3.13: Mediation Analysis for SCP - Conglomerates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Structure–Performance (without conduct)	0.261***	-0.184***	0.145**	-0.933***	0.189***	-0.349***	0.175***	-0.877***	0.883***	-0.501***	0.327***	-0.809***
	(0.034)	(0.012)	(0.074)	(0.062)	(0.005)	(0.015)	(0.066)	(0.023)	(0.334)	(0.019)	(0.011)	(0.033)
Structure–Performance (with conduct)	0.114***	-0.021***	0.057***	-0.106***	0.129***	-0.257***	0.086***	-0.210***	0.458***	-0.108***	0.231***	-0.387***
	(0.008)	(0.000)	(0.004)	(0.000)	(0.009)	(0.018)	(0.000)	(0.000)	(0.000)	(0.000)	(0.015)	(0.076)
Coefficient on Conduct (in S–C–P model)	-0.353***	0.757***	-0.354***	0.804***	-0.350***	0.644***	-0.445***	0.616***	-0.465***	0.638***	-0.391***	0.557***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Structure–Conduct	-0.025***	-0.025***	-0.016***	-0.016***	-0.115***	-0.115***	-0.025***	-0.025***	-0.016***	-0.016***	-0.115***	-0.115***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Complementary tests												
Sobel test	-0.353***	0.781***	-0.354***	0.804***	-0.350***	0.722***	-0.445***	0.631***	-0.465***	0.654***	-0.391***	0.567***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Aroian test	-0.025***	-0.025***	-0.016***	-0.016***	-0.115***	-0.115***	-0.025***	-0.025***	-0.016***	-0.016***	-0.115***	-0.115***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Goodman test	0.878***	-0.195***	-0.566***	0.129***	-0.403***	0.083***	-0.111***	0.157***	-0.744***	0.105***	-0.045***	0.065***
	(0.005)	(0.001)	(0.025)	(0.005)	(0.076)	(0.002)	(0.002)	(0.018)	(0.014)	(0.001)	(0.000)	(0.000)
Bootstrapped test												
Indirect Effect	-0.878***	-0.195***	-0.566***	0.129***	-0.403***	0.083***	-0.111***	0.157***	-0.744***	0.105***	-0.045***	0.065***
	(0.005)	(0.001)	(0.025)	(0.005)	(0.076)	(0.002)	(0.002)	(0.018)	(0.015)	(0.00)	(0.000)	(0.000)
Percentile CI (95%) - Lower	-0.139	0.101	-0.828	0.079	-0.121	-0.868	-0.611	-0.154	-0.391	-0.097	-0.415	-0.141
Upper	-0.045	0.297	-0.340	0.187	0.043	0.235	0.329	0.527	0.205	0.323	0.258	0.359
Bias-corrected CI (95%) - Lower	-0.135	0.098	-0.826	0.078	-0.117	-0.971	-0.624	-0.134	-0.397	-0.099	-0.556	-0.070
Upper	-0.042	0.294	-0.336	0.185	0.047	0.225	0.319	0.555	0.201	0.322	0.139	0.487
Bias-corrected and accelerated CI (95%) - Lower	-0.134	0.097	-0.824	0.077	-0.119	-0.957	-0.632	-0.139	-0.399	-0.101	-0.559	-0.072
Upper	-0.042	0.293	-0.334	0.185	0.046	0.226	0.314	0.547	0.198	0.322	0.138	0.482

This table presents the mediation analysis based on the SAG and the Bootstrapped tests. Models 1, 3, & 5 (2, 4, & 6) are estimated using the PE SCORE (PE RANK) as performance measures and Conduct captured via the PRH. Models 7, 9, & 11 (8, 10, & 12) are estimated using the CE SCORE (CE RANK) as performance measures. Market structure is captured via the HHI, HHI Dual and CR5 under Models 1 & 2 (5 & 6); 3 & 4 (7 & 8); and 5 & 6 (11 & 12) respectively. Model specifications include all other control variables, year and firm fixed effects. Significance indicators: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.14: Mediation Analysis for SCP – Non-Conglomerates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Structure–Performance (without conduct)	0.431***	-0.174***	-0.117***	-0.883***	0.160***	-0.337***	0.672***	-0.431***	0.311***	-0.214**	0.252***	-0.451***
	(0.010)	(0.004)	(0.005)	(0.018)	(0.001)	(0.005)	(0.011)	(0.009)	(0.006)	(0.004)	(0.019)	(0.163)
Structure–Performance (with conduct)	0.109	-0.020	0.054	-0.103	0.125	-0.250	0.371	-0.395**	0.237	-0.117**	0.164	-0.372**
	(0.197)	(0.020)	(0.041)	(0.100)	(0.103)	(0.204)	(0.881)	(0.202)	(0.419)	(0.046)	(0.195)	(0.163)
Coefficient on Conduct (in S–C–P model)	-0.352***	0.753***	-0.353***	0.796***	-0.349***	0.645***	-0.668***	0.142***	-0.676***	0.244***	-0.645***	0.110***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Structure–Conduct	-0.030***	-0.030***	-0.019***	-0.019***	-0.185***	-0.185***	-0.030***	-0.030***	-0.019***	-0.019***	-0.185***	-0.185***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.004)	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)	(0.004)	(0.004)
Complementary tests												
Sobel test	-0.352***	0.773***	-0.353***	0.796***	-0.349***	0.645***	-0.668***	0.142***	-0.676***	0.244***	-0.645***	0.110***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Aroian test	-0.030***	-0.030***	-0.019***	-0.019***	-0.185***	-0.185***	-0.030***	-0.030***	-0.019***	-0.019***	-0.185***	-0.185***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.004)	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)	(0.004)	(0.004)
Goodman test	-1.050***	2.307**	-0.660***	1.489***	-0.646**	0.132***	-1.993***	3.496***	-1.265***	2.242***	-0.119***	0.203***
	(0.076)	(1.674)	(0.039)	(0.087)	(0.121)	(0.025)	(0.266)	(0.324)	(0.159)	(0.184)	(0.026)	(0.040)
Bootstrapped test												
Indirect Effect	-1.050***	2.307**	-0.660***	1.489***	-0.646**	0.132***	-1.993***	3.496***	-1.265***	2.242***	-0.119***	0.203***
	(0.076)	(1.674)	(0.039)	(0.087)	(0.121)	(0.025)	(0.266)	(0.356)	(0.179)	(0.199)	(0.037)	(0.047)
Percentile CI (95%) - Lower	-0.202	0.066	-0.116	0.061	-0.021	-0.166	-0.810	-0.894	-0.473	-0.380	-0.070	-0.029
Upper	-0.031	0.426	-0.027	0.257	0.075	0.403	0.249	0.096	0.146	0.057	0.297	0.087
Bias-corrected CI (95%) - Lower	-0.198	0.069	-0.116	0.065	-0.019	-0.182	-0.935	-0.318	-0.551	-0.860	-0.107	-0.014
Upper	-0.027	0.428	-0.027	0.265	0.086	0.389	0.165	0.108	0.109	0.063	0.130	0.112
Bias-corrected and accelerated CI (95%) - Lower	-0.197	0.063	-0.115	0.063	-0.019	-0.183	-0.999	-0.334	-0.604	-0.949	-0.112	-0.015
Upper	-0.026	0.423	-0.026	0.260	0.086	0.386	0.140	0.108	0.094	0.063	0.121	0.110

This table presents the mediation analysis based on the SAG and the Bootstrapped tests. Models 1, 3, & 5 (2, 4, & 6) are estimated using the PE SCORE (PE RANK) as performance measures and Conduct captured via the PRH. Models 7, 9, & 11 (8, 10, & 12) are estimated using the CE SCORE (CE RANK) as performance measures. Market structure is captured via the HHI, HHI Dual and CR5 under Models 1 & 2 (5 & 6); 3 & 4 (7 & 8); and 5 & 6 (11 & 12) respectively. Model specifications include all other control variables, year and firm fixed effects. Significance indicators: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.4.8. Market structure, bank conduct and performance: board size (large vs small vs ideal)

In this section, I examine whether good corporate governance matters for the validity of the SCP hypothesis. The board of directors serves as the linchpin for an effective internal governance framework. They have key responsibility for risk management and setting the tone for a bank's conduct (e.g., risk-taking culture) (Srivastav and Hagendorff, 2016). Good corporate governance (i.e., quality of board monitoring, advisory and decision-making) has an important effect on bank conduct, risk and performance (Adams and Mehran, 2012; Pathan and Faff, 2013). I propose two opposing notions. A supportive notion suggests that good corporate governance may enhance the positive SCP relationship. When bank conduct and/or risk-taking behaviour/propensity are approved by the board, a bank with good governance effectively implements these activities (Wu and Shen, 2019). Accordingly, this implementation increases the effect of interbank market structure on bank conduct and ultimately performance. The opposing notion stresses that good governance may rather decrease the positive relationship. Good governance tends to balance manager-shareholder interests. When a manager's conduct shows a tendency to take risks via collusion or anti-competitive pricing, a bank with strong independent directors will effectively mitigate the risk-taking behaviour/conduct or even recruit a chief risk officer to safeguard against that potential risk. Therefore, good governance will emphasize shareholders' interests to mitigate the manager's conduct/behaviour by preventing any abuse of their power to take risks.

The literature gives opposing views on how a bank's board size affects the overall effectiveness of the board. In one breadth, larger boards increase the pool of relevant expertise, connections and resources that add firm value given that banking business has grown more complex and opaque over time (Upadhyay and Sriram, 2011). On the other hand, smaller boards may improve governance since large boards may become less effective at monitoring due to free-rider problems (e.g., coordination, control, and flexibility in decision-making) (Pathan, 2009). However, another school of thought holds that effective boards converge around an ''ideal'' size of 10–12 members (Coles et al., 2008; Adams and Mehran, 2012). I follow the governance literature (e.g., Adams and Mehran, 2012; Wu and Shen, 2019) and use board size, the number of directors on the board, to proxy for corporate governance. I classify firms into banks with larger (i.e., top one-third quantile -75th P), smaller (i.e., bottom one-third quantile -25th P) and ideal board size (10–12 members). Further, I include a control for board independence into the estimation using the number of outside directors.

First, the results in this section are consistent with and complementary to the main findings that interbank market structure impacts significantly on bank conduct and performance. However, it is worth noting that the magnitude of the impact on the bank conduct coefficient is greater for banks with smaller boards, followed by larger and ideal board size. The implication is that board size is a key dimension of bank conduct and competition. Banks with smaller boards behave more anti-competitively under higher interbank market concentration perhaps because their risk management systems are adequate to respond aggressively to market changes, or smaller bank boards are unable to effectively monitor and control bank risk-taking behaviour/conduct (Pathan, 2009; Srivastav and Hagendorff, 2016). Although bank performance is significantly positive (score) or negative (rank) in the structure-performance estimation, the significance of the coefficients indicates that market structure matters more for banks with smaller boards both in terms of profit and cost efficiency. This outcome confirms the position of Guest (2008) and Coles et al. (2008) that large boards positively impact bank performance, especially where banks require more advising, such as complex banks that operate in complex and/or multiple markets/segments. Repeating the estimation on the ideal board sample also shows that market structure matters for bank performance just as in large bank boards. For the key SCP validity test, I observe a reduction in the market structure coefficients of large bank boards. For smaller bank boards, I observe that the market structure coefficients remain significant under profit efficiency but insignificant for cost efficiency. However, there’s no consistent evidence of a decline in the coefficients. Although the market structure coefficients also remain significant for ideal bank boards, there’s still no consistent evidence of a decline in the coefficients. Further, the insignificant conduct coefficients in the cost efficiency estimations indicate that the SCP hypothesis may not be applicable to banks with ideal boards. The implication of this result is that bank conduct partially mediates the structure-performance relationship only for large bank boards. Hence, the interbank market structure is both profit and cost efficient for large bank boards, and thus encourages greater participation of banks with large boards in financial networks.

Further analysis via the Sobel, Aroian and Goodman test statistics as well as the bootstrapped estimates of the indirect effect indicate that the mediation effect of bank conduct is robust for large bank boards. A probable explanation for these results is that large bank boards will engage in anti-competitive behaviour given their access to greater information, expertise, connections and resource so as to mitigate asymmetric information problems. This outcome is also not surprising given that bank board tend to be larger for UK banks but less effective relative[16] to that of other listed firms or banks in other jurisdictions (Guest, 2008). Further, a bank's board may also grow larger by incorporating directors from subsidiaries/affiliates (signs of interdependency and collusion) to boost information flow (Adams and Mehran, 2012). For small and ideal bank boards, although interbank market structure affects bank performance, the evidence suggests that the impact on performance is not through conduct but via other measures such as effective monitoring predisposition and/or bank inability to override regulatory policies/reforms (Pathan and Faff, 2013; Berger et al., 2016). These findings confirm the position of prior studies (e.g., Coles et al., 2008; Adams and Mehran, 2012) that firm's economic environment (i.e., monitoring mechanisms, degree of concentration) influences the effectiveness of board size on bank conduct or behaviour, and consequently bank performance. Further, I confirm the presence of an ideal board size by showing that beyond a board size of 12, free-rider problems may overshadow the gains of extensive knowledge development by a large board and thus intensify the likelihood of anti-competitive bank conduct and risk-taking (Wang and Hsu, 2013).

Taken together, the results suggest that corporate governance matters for the validity of the SCP hypothesis and to policymakers. In recent years, policymakers and regulators have stressed on specific governance shortcomings[17] but failed to address more fundamental governance flaws (Kashyap et al., 2008; Srivastav and Hagendorff, 2016). Inherently, the complexity and opaqueness of banking business and financial markets exacerbates information asymmetry problems and thus necessitates more effective monitoring (Macey and O'hara, 2003; Levine, 2004). Furthermore, as specified in

[16] Board directors are seldomly held lawfully accountable for failure to perform their responsibilities; their roles are regarded as largely advisory rather than monitoring (e.g., Franks et al., 2001; Ozkan, 2007) and boards comprise low proportions of outside directors - independence (Guest, 2008).

[17] The Walker Review (Walker, 2009) specifies the key composition, qualifications and compensation contracts for board members in UK financial institutions.

Marques and Oppers (2014), policy research must focus on addressing the impact of other key governance mechanisms on bank conduct (e.g., risk-taking propensity).

Table 3.15: Mediation Analysis for SCP – Banks with larger board size

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Structure–Performance (without conduct)	0.286**	-0.277***	0.299**	-0.718***	0.431***	-0.550***	0.299***	-0.186***	0.151***	-0.907***	0.603***	-0.508***
	(0.132)	(0.005)	(0.118)	(0.032)	(0.135)	(0.008)	(0.018)	(0.000)	(0.000)	(0.042)	(0.031)	(0.022)
Structure–Performance (with conduct)	0.103***	-0.206***	0.203***	-0.584***	0.223***	-0.369***	0.255*	-0.154***	0.087*	-0.742***	0.640*	-0.540***
	(0.006)	(0.005)	(0.004)	(0.004)	(0.072)	(0.090)	(0.113)	(0.009)	(0.051)	(0.044)	(0.336)	(0.162)
Coefficient on Conduct (in S–C–P model)	-0.352***	0.779***	-0.352***	0.701***	-0.349***	0.665***	-0.150**	0.154**	-0.154**	0.156**	-0.140*	0.149**
	(0.001)	(0.002)	(0.001)	(0.005)	(0.001)	(0.001)	(0.073)	(0.072)	(0.074)	(0.072)	(0.071)	(0.071)
Structure–Conduct	-0.037***	-0.037***	-0.023***	-0.023***	-0.264***	-0.264***	-0.037***	-0.037***	-0.023***	-0.023***	-0.264***	-0.264***
	(0.008)	(0.008)	(0.005)	(0.005)	(0.010)	(0.010)	(0.008)	(0.008)	(0.005)	(0.005)	(0.010)	(0.010)
Complementary tests												
Sobel test	-0.351***	0.771***	-0.352***	0.795***	-0.349***	0.716***	-0.621*	0.759*	-0.644*	0.781*	-0.571*	0.710**
	(0.001)	(0.005)	(0.001)	(0.005)	(0.001)	(0.004)	(0.585)	(0.620)	(0.589)	(0.621)	(0.377)	(0.414)
Aroian test	-0.042***	-0.042***	-0.025***	-0.025***	-0.311***	-0.311***	-0.042***	-0.042***	-0.025***	-0.025***	-0.311***	-0.311***
	(0.002)	(0.002)	(0.005)	(0.005)	(0.028)	(0.028)	(0.002)	(0.002)	(0.005)	(0.005)	(0.028)	(0.010)
Goodman test	-1.469***	3.230***	-0.895***	2.024***	-1.084***	2.225***	-2.610***	3.179***	-1.639***	1.987***	-0.178***	0.221***
	(0.061)	(0.135)	(0.031)	(0.071)	(0.098)	(0.202)	(0.386)	(0.291)	(0.233)	(0.172)	(0.032)	(0.028)
Bootstrapped test												
Indirect Effect	-1.469***	3.230***	-0.895***	2.024***	-1.084***	2.225***	-2.610***	3.179***	-1.639***	1.987***	-0.178***	0.221***
	(0.061)	(0.135)	(0.031)	(0.071)	(0.098)	(0.202)	(0.415)	(0.310)	(0.246)	(0.182)	(0.040)	(0.033)
Percentile CI (95%) - Lower	-0.228	0.198	-0.136	0.133	-0.230	0.021	-0.117	-0.196	-0.698	-0.124	-0.100	-0.178
Upper	-0.088	0.511	-0.059	0.308	-0.011	0.470	0.056	0.935	0.327	0.573	0.048	0.831
Bias-corrected CI (95%) - Lower	-0.221	0.189	-0.131	0.128	-0.213	-0.007	-0.118	-0.186	-0.713	-0.119	-0.113	-0.122
Upper	-0.083	0.498	-0.057	0.298	0.017	0.433	0.053	0.950	0.318	0.576	0.038	0.921
Bias-corrected and accelerated CI (95%) - Lower	-0.219	0.183	-0.130	0.125	-0.213	-0.007	-0.120	-0.188	-0.727	-0.120	-0.114	-0.126
Upper	-0.082	0.487	-0.056	0.295	0.019	0.427	0.053	0.948	0.314	0.575	0.037	0.917

This table presents the mediation analysis based on the SAG and the Bootstrapped tests. Models 1, 3, & 5 (2, 4, & 6) are estimated using the PE SCORE (PE RANK) as performance measures and Conduct captured via the PRH. Models 7, 9, & 11 (8, 10, & 12) are estimated using the CE SCORE (CE RANK) as performance measures. Market structure is captured via the HHI, HHI Dual and CR5 under Models 1 & 2 (5 & 6); 3 & 4 (7 & 8); and 5 & 6 (11 & 12) respectively. Model specifications include all other control variables, year and firm fixed effects. Significance indicators: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.16: Mediation Analysis for SCP – Banks with smaller board size

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Structure–Performance (without conduct)	0.545**	-0.152***	0.443**	-0.121**	0.850**	-0.315**	0.154***	-0.340**	0.767**	-0.620**	0.321**	-0.622***
	(0.280)	(0.019)	(0.244)	(0.060)	(0.452)	(0.122)	(0.012)	(0.152)	(0.496)	(0.419)	(0.204)	(0.274)
Structure–Performance (with conduct)	0.908***	-0.183***	0.436***	-0.441***	0.215***	-0.340	0.182	-0.589	0.940	-0.441	0.345	-0.466
	(0.181)	(0.009)	(0.010)	(0.038)	(0.002)	(0.310)	(0.177)	(0.631)	(0.852)	(0.385)	(0.313)	(0.448)
Coefficient on Conduct (in S–C–P model)	-0.346***	0.720***	-0.347***	0.506***	-0.345***	0.629***	-0.665**	0.380**	-0.685**	0.500**	0.627**	-0.562**
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.326)	(0.176)	(0.333)	(0.351)	(0.313)	(0.391)
Structure–Conduct	-0.042**	-0.042**	-0.025**	-0.025**	-0.377*	-0.377*	-0.042**	-0.042**	-0.025**	-0.025**	-0.377*	-0.377*
	(0.020)	(0.020)	(0.011)	(0.011)	(0.280)	(0.280)	(0.020)	(0.020)	(0.011)	(0.011)	(0.280)	(0.280)
Complementary tests												
Sobel test	-0.346***	0.720***	-0.347***	0.742***	-0.345***	0.680***	-0.665**	0.986**	-0.685**	0.500**	0.627**	-0.562**
	(0.004)	(0.004)	(0.004)	(0.014)	(0.004)	(0.012)	(0.326)	(0.524)	(0.333)	(0.351)	(0.313)	(0.391)
Aroian test	-0.042*	-0.042*	-0.025**	-0.025**	-0.377	-0.377	-0.042*	-0.042*	-0.025**	-0.025**	-0.377	-0.377
	(0.020)	(0.020)	(0.011)	(0.011)	(0.280)	(0.280)	(0.020)	(0.020)	(0.011)	(0.011)	(0.280)	(0.280)
Goodman test	-0.145	0. 302	0.879*	1.879	-1.302	0.256	0.279	0.414	1.736	2.596	0.236	0.342
	(0.149)	(0.316)	(0.764)	(1.669)	(2.443)	(0.483)	(0.319)	(0.478)	(1.731)	(2.620)	(0.460)	(0.669)
Bootstrapped test												
Indirect Effect	-0.145	0. 302	0.879*	1.879	-1.302	0.256	0.279	0.414	1.736	2.596	0.236	0.342
	(0.149)	(0.321)	(0.765)	(1.697)	(2.446)	(0.491)	(0.350)	(0.529)	(1.882)	(2.620)	(0.514)	(0.759)
Percentile CI (95%) - Lower	-0.432	-0.159	-0.024	-0.546	-0.531	-0.499	-0.990	-0.283	-0.596	-0.997	-0.120	-0.079
Upper	0.068	-0.093	0.223	0.052	0.250	1.044	0.182	0.017	0.061	0.095	0.057	0.190
Bias-corrected CI (95%) - Lower	-0.404	-0.147	-0.023	-0.415	-0.519	-0.552	-1.201	-0.171	-0.683	-0.547	-0.143	-0.047
Upper	0.081	-0.095	0.249	0.055	0.265	1.006	0.088	0.020	0.032	0.109	0.041	0.246
Bias-corrected and accelerated CI (95%) - Lower	-0.401	-0.156	-0.023	-0.437	-0.519	-0.555	-1.191	-0.174	-0.686	-0.534	-0.141	-0.052
Upper	0.082	-0.093	0.252	0.055	0.265	1.005	0.090	0.020	0.032	0.109	0.043	0.238

This table presents the mediation analysis based on the SAG and the Bootstrapped tests. Models 1, 3, & 5 (2, 4, & 6) are estimated using the PE SCORE (PE RANK) as performance measures and Conduct captured via the PRH. Models 7, 9, & 11 (8, 10, & 12) are estimated using the CE SCORE (CE RANK) as performance measures. Market structure is captured via the HHI, HHI Dual and CR5 under Models 1 & 2 (5 & 6); 3 & 4 (7 & 8); and 5 & 6 (11 & 12) respectively. Model specifications include all other control variables, year and firm fixed effects. Significance indicators: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.17: Market Structure, Conduct and Performance – Banks with ideal board size

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Structure–Performance (without conduct)	0.292***	-0.184***	0.169***	-0.935***	0.194***	-0.349***	0.258***	-0.297***	0.132***	-0.151***	0.436***	-0.533***
	(0.003)	(0.001)	(0.001)	(0.007)	(0.005)	(0.002)	(0.005)	(0.006)	(0.004)	(0.003)	(0.143)	(0.103)
Structure–Performance (with conduct)	0.113***	-0.205***	0.563***	-0.106***	0.228***	-0.356***	0.258***	-0.403***	0.133***	-0.117***	0.435***	-0.379***
	(0.001)	(0.001)	(0.006)	(0.006)	(0.001)	(0.002)	(0.008)	(0.014)	(0.004)	(0.004)	(0.001)	(0.001)
Coefficient on Conduct (in S–C–P model)	-0.352***	0.752***	-0.353***	0.801***	-0.349***	0.640***	0.123	-0.142	-0.149	-0.160	0.887	0.114
	(0.000)	(0.004)	(0.000)	(0.004)	(0.000)	(0.002)	(0.412)	(0.482)	(0.414)	(0.627)	(1.064)	(0.398)
Structure–Conduct	-0.024***	-0.024***	-0.015***	-0.015***	-0.099***	-0.099***	-0.024***	-0.024***	-0.015***	-0.015***	-0.099***	-0.099***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.014)	(0.014)	(0.001)	(0.001)	(0.000)	(0.000)	(0.014)	(0.014)
Complementary tests												
Sobel test	-0.352***	0.778***	-0.353***	0.801***	-0.349***	0.719***	0.123	-0.570	-0.149	-0.603	0.887	0.479
	(0.000)	(0.006)	(0.000)	(0.004)	(0.000)	(0.002)	(0.412)	(0.707)	(0.414)	(0.709)	(1.064)	(0.398)
Aroian test	0.024***	0.024***	0.015***	0.015***	0.099***	0.099***	0.024***	0.024***	0.015***	0.015***	0.099***	0.099***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.014)	(0.014)	(0.001)	(0.001)	(0.000)	(0.000)	(0.014)	(0.014)
Goodman test	-0.839*	1. 853	-0.546*	1.239**	-0.345	0.071	0.293	0.136	0.230	0.932	0.088	0.047
	(0.586)	(1.301)	(0.301)	(0.689)	(0.937)	(0.193)	(0.223)	(0.193)	(1.453)	(1.211)	(0.095)	(0.145)
Bootstrapped test												
Indirect Effect	-0.839*	1. 853	-0.546*	1.239**	-0.345	0.071	0.293	0.136	0.230	0.932	0.088	0.047
	(0. 586)	(1.301)	(0.302)	(0.691)	(0.938)	(0.194)	(0.272)	(0.226)	(1.660)	(1.211)	(0.095)	(0.145)
Percentile CI (95%) - Lower	-0.147	0.061	-0.889	0.063	-0.134	-0.152	-0.555	-0.201	-0.345	-0.131	-0.040	-0.022
Upper	-0.029	0.319	-0.254	0.202	0.070	0.260	0.514	0.571	0.320	0.359	0.043	0.040
Bias-corrected CI (95%) - Lower	-0.146	0.052	-0.889	0.060	-0.128	-0.171	-0.517	-0.183	-0.316	-0.119	-0.033	-0.012
Upper	-0.027	0.311	-0.254	0.199	0.078	0.250	0.556	0.608	0.341	0.375	0.050	0.055
Bias-corrected and accelerated CI (95%) - Lower	-0.145	0.051	-0.885	0.059	-0.128	-0.167	-0.525	-0.182	-0.322	-0.118	-0.034	-0.012
Upper	-0.027	0.309	-0.252	0.197	0.076	0.251	0.548	0.610	0.337	0.376	0.049	0.053

This table presents the mediation analysis based on the SAG and the Bootstrapped tests. Models 1, 3, & 5 (2, 4, & 6) are estimated using the PE SCORE (PE RANK) as performance measures and Conduct captured via the PRH. Models 7, 9, & 11 (8, 10, & 12) are estimated using the CE SCORE (CE RANK) as performance measures. Market structure is captured via the HHI, HHI Dual and CR5 under Models 1 & 2 (5 & 6); 3 & 4 (7 & 8); and 5 & 6 (11 & 12) respectively. Model specifications include all other control variables, year and firm fixed effects. Significance indicators: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.5. Conclusions

This chapter provides empirical evidence for the validity of the SCP hypothesis in the context of the interbank market and the UK given the significant and ongoing structural changes in its banking industry. This study utilises an approach that incorporates the intermediating role of bank conduct in the structure-performance nexus, a key methodological issue in prior or traditional SCP studies. The results show that interbank market structure provides a channel for banks operating in the UK to collude and/or engage in monopolistic pricing in the market for bank and business loans. Specifically, interbank market structure affects bank conduct or behaviour, to ultimately increase bank performance. These findings are robust to alternative measures of market structure, bank conduct and performance. Further analysis indicates that collusion and other anti-competitive behaviours in the interbank market exacerbate incentives for foreign and conglomerate banks to enter, although domestic banks can still make profits by supplying liquidity to small banks that enter but lack liquidity. Lastly, the results show that good governance matters significantly for the validity of the positive SCP hypothesis. Large bank boards are more likely to conduct/behave anti-competitive given their access to greater information, expertise, connections/affiliations and resources.

Overall, the findings have important implications for policymakers. The SCP paradigm proposes that when a small group of firms dominate a market in terms of shares, the likelihood of collusive behaviour amongst these firms increases. Accordingly, the SCP hypothesis necessitate that foreign entry and consolidation activities are effectively monitored and regulated since concentration weakens competition, and results in market inefficiency (e.g., collusion and monopoly profits). These implications are crucial for the UK banking industry and interbank market given the ongoing and unprecedented shift towards a highly consolidated as well as concentrated market structure. Moreover, bank profitability continues to improve while cost efficiency reduces after the implementation of several unconventional policy measures post financial crisis and the LIBOR scandal. Indeed, these facts increase skepticism about antitrust policies particularly if consolidation activities are motivated by the desire to enhance bank profitability via monopolistic pricing. Then such policies are most likely to hurt the economy by making the interbank and intermediation process very costly.

Chapter 4

Bank business models, failure risk and earnings opacity: A short- versus long-term perspective

4.1. Introduction and background

"If you're a supervisor you need to understand the business model … The root of it is still how are you earning your money; how are you managing your balance sheet?" (Andrew Bailey, Chief Executive of the Financial Conduct Authority).

The above statement underscores the importance of business models as mechanisms for earnings management and a firm's value creation. Generally, banks are highly diversified and strategically distinct from one another. They seek to achieve a competitive position over others by leveraging their strengths in terms of access to specialised resources, market prospects and accessibility, and key managerial competences. The conscious and competitive pursuit of these goals drive their choice of business model strategies which often encompass their distinct intermediation activities and inter alia, their balance sheet composition. By ensuring a balance between available opportunities and the business model, a bank can forge a stronger foundation for healthy and sustainable profitability. Likewise, the choice of business models or changes to the business mix of a poorly performing bank may have systematic implications for the banking sector. Together, these factors exacerbate the relevance of bank's business model strategy to policymakers. Access to information on business models can enable regulatory and prudential supervisors to better gauge a bank's ability to generate reliable earnings that would boost the banking system and banks stability. Further, where business model-specific risk factors exist, the distribution of business models across the banking sector can signal a concentration of risk exposures in certain segments.

Despite this, the inherent opacity of bank balance sheet structure hinders regulation and market discipline of banks as it restricts the ability of external parties to accurately value and assess their risk-taking propensity (Jungherr, 2018). Accordingly, recent evidence suggests an unprecedented and ongoing increase in bank regulatory reforms, such as the comprehensive Basel III framework which aims to ensure greater disclosure, transparency, competition and strengthen the resilience of banks (Fosu et al., 2018). The literature highlights an increasing trend in research on bank earnings opacity and competition post financial crisis (e.g., Zhao et al., 2013; Jiang et al., 2016; Jungherr, 2018). Indeed, the key factors that propagated and amplified the financial crisis include increased complexity in bank business models (Flannery et al., 2013), increased risk-taking propensity in response to competitive pressures and regulations (Fosu et al., 2018), and the greater intermediation and delegated monitoring activities of banks (Mergaerts and Vander Vennet, 2016). A fundamental channel to address bank opacity, particularly earnings opacity, is to restrict banks' scope for discretionary accounting choices which enable them to hold complicated financial assets and postpone the recognition of any expected losses on their balance sheets. However, surprisingly, the empirical evidence lacks any formal tests to specifically justify the different business model choice of banks on earnings opacity and their motivations to report high quality accounting information, particularly considering the highly heterogeneous landscape of business model choices available to European banks.

This chapter therefore seeks to provide the first assessment of the impact of bank business models on the degree of bank earnings opacity. The quantity and quality of accounting information is fundamental to global financial sector and economic growth. However, a key threat to the quality of available information is earnings opacity. I contend that the degree of bank earnings opacity – i.e., how little information there is about the firm's true earnings position or performance (Bhattacharya et al., 2003), is dependent on the choice of bank business model: the retail orientation (RETAIL), the degree of functional diversification (DIVERSIFICATION), and the wholesale orientation (WHOLESALE) of banks. Simply, the choice of business model drives a bank's decision to manage their financial statements to smooth earnings, circumvent capital requirements, and/or decrease taxes (Beatty et al., 2002; Jiang et al., 2016). Further, I investigate the extent to which the interaction between bank business model and earnings opacity is conditional on bank failure risk. As liquidity is created through a mismatch of long-term assets to short-term liabilities, liquidity creation exposes banks to failure risk which induce banks to manipulate their financial statements, and thus increases overall bank opacity. Also, I consider whether the choice of accounting standards, the effectiveness of the auditor's role in safeguarding reporting credibility, and financial conglomeration have key implications for the business model effects on earnings opacity.

This chapter uses a sample of 137 banks in the UK with data spanning 2010 to 2018. To examine bank business models, I employ two alternative approaches to capture the permanence and the scope of business model strategies. In the first approach, I the use of individual bank characteristics to directly explain earnings opacity. The second approach employs the factor analysis to determine three key factors that capture the inherent latent strategies of business models: the retail orientation (RETAIL), the degree of functional diversification (DIVERSIFICATION), and the wholesale orientation (WHOLESALE) of banks. The retail-oriented model is more transparent and quite stable, in the sense that retail deposits represent a highly stable source of bank funding and thus, balance sheet characteristics of traditional retail banks change less. The wholesale-oriented model, where banks hold larger securities portfolios funded by the interbank and wholesale markets, is less stable. Likewise, the diversified business model is characterised by a highly diversified asset and income structure. To explore the business model effects on earnings opacity, the study explicitly distinguishes between the short-term (within) and long-term (between) effects – temporal stableness versus stableness across banks over time. The study also used various alternative measures of earnings opacity to test the robustness of the business model effects.

The findings suggest that retail-oriented business models decrease the likelihood earnings management practices in the short-term due to the increased transparent and stableness of retail deposits. However, the funding stability advantages may be eroded over the long-term and thus, increasing incentives for earnings management over the long-term. In contrast, wholesale-oriented business models increase the probability of earnings manipulation both in the short- and long-term. Although wholesale financiers may develop better capabilities and incentives to monitor and discipline banks and attempts can be made through highly sophisticated rules to improve market confidence in the long-term, wholesale funding sources will always be subjected to market-wide liquidity shocks and thus, remain highly volatile. While bank business models characterised by greater degree of functional diversification are likely to lower earnings manipulation in the short-term, the long-term incentives cannot be mitigated. Further analysis shows that although banks characterized by high capital ratios are less likely to engage in earnings management practices, the Tier I capital as championed by the Basel framework serves as a more effective tool towards safeguarding bank's financial viability and mitigating bank earnings management practices over the long-term.

In examining whether low failure risk can mitigate the inherent business models effects on earnings management practices, I find that retail-oriented funding provides inherent funding stability and transparency, and thus, when complemented by low failure risk levels should further mitigate any incentives for earnings management. In terms of diversification of income sources, I find that because larger liquid positions reduce any inherent risk of distress, a complement by strengthening solvency levels should further mitigate any incentives for earnings management. Over the long-term, increasing organizational complexity due to larger share of non-interest income may worsen information asymmetry and agency problems. However, with greater stability, scrutiny and solvency levels, any adverse earnings practices associated with a highly diversified asset and income structure are mitigated. Under wholesale-oriented banking, I find that although wholesale-oriented banks may be riskier, the price of wholesale funds also adjusts rapidly to reflect bank's riskiness and therefore, greater bank solvency levels will promptly be incorporated into valuations to lessen the incentives for short-term earnings management. Also, as wholesale financiers develop better capabilities towards understanding accounting information, more sound and solvent banks would have less long-term earnings manipulation.

This chapter makes five key contributions to literature. First, the study provides the first evidence on the relationship between bank business model strategies and earnings opacity. Secondly, the study adda to the growing literature on business model strategies by providing a short- vs long-term perspective under which key implications for earnings opacity are derived. Third, this study complements existing approaches of identifying business models by employing factor analysis to robustly identify and account for the impact of key business model strategies on earnings opacity. Unlike Köhler (2015) and Mergaerts and Vander Vennet, (2016) who use two variables to identify business models, this study uses three variables with the third variable accounting for the reliance on short-term wholesale funding in the UK and Europe. Fourth, in line with recent developments, this study extends the confines of the business model nexus to incorporate issues related to accounting rules and reforms, and integrate UK's unique banking structure (i.e., accounting standards, audit qualification and conglomerate-subsidiary effect). It is imperative for policy makers to examine whether these factors can mitigate or worsen the inherent riskiness of business models towards eradicating incentives for earnings management. If they do, then supervisory authorities should monitor banks prudently and necessitate proactive steps towards augmenting or increasing the regulatory ratios when they decline, as envisaged under the prompt corrective action feature of the Federal Deposit Insurance Corporation Improvement Act (FDICIA).

Finally, this chapter pulls together the literature on business models and bank failure to explain earnings opacity of banks. Although business models and bank failure have documented strong theoretical implications (see e.g., Kohler, 2015), this chapter, to the best of my knowledge, is the first to examine their joint effects on earnings opacity. By doing so, the chapter helps to address potential regulatory and supervisory concerns about whether, and to what extent, bank failure risk exacerbates misreporting of financial information and thus hindering banks' disclosure requirements. Simply, I shed light on whether there is an optimal business model and a level of failure risk at which opacity is less costly in banking. This question is crucial in the sense that all three constructs (i.e. business model, bank failure and earning opacity) limit bank monitoring and can have extreme cost implications (Bushman and Williams, 2015).

The policy implications of this chapter are relevant in the context of the UK banking system given the significant and ongoing regulatory changes in the banking industry. Similar to other jurisdictions, the financial crisis was attributed to poor institutional practices of banks particularly involving the lack of disclosure, transparency and fair competition amongst the major global banks. For instance, Northern Rock –UK's fastest-growing mortgage bank at the time operated a business model with high reliance on non-retail or wholesale funding, became the first high-profile casualty of the crisis when it collapsed in September 2007. Moreover, although the wholesale funding model has cues such as the maturity and sourcing, a detailed breakdown of the model is not disclosed in the annual reports (Shin, 2009). According to Bank of England ex-governor Mervyn King, "their business model was dead" while pointing to deep failures within the regulatory framework. Likewise, Andrew Bailey, Chief Executive of the Financial Conduct Authority (FCA) described Northern Rock's business model as the "warehousing model" which necessitated the sale of bonds every three months. The House of Common's (2009) report recognizes supervisory failure on the part of the Financial Services Authority (FSA) for not acting proactively when it identified Northern Rock's funding model as systemically exposing the banking industry to substantial risks. Again, within the context of the UK, evidence emerged recently to suggest that the London Interbank Offered Rate (LIBOR) scandal is one of the key causes of the financial crisis (Vaughan and Finch, 2017; Fosu et al., 2018). The period envisaged a rise in regulatory lapses that stimulated greater collusion by mandated global banks to deliberately manipulate the LIBOR (Duffie and Stein, 2015). More importantly, the crisis period was characterised by aggravated liquidity hoarding due to fear of counterparty risk in the interbank market as bank business models allowed banks to delay and hide disclosure of losses on Asset Backed Securities from credit and liquidity risk (Barrell and Davis, 2008). These and many other opaque bank practices have recently been identified, usually leading to criminal prosecutions, fines and long-term imprisonments (Vaughan and Finch, 2017). Consequently, raising critical issues that necessitate supervisory attention and intervention.

The rest of the chapter proceeds as follows. Section 4.2 presents the theories and hypothesis underlining the analysis. Section 4.3 discusses the methodology used to classify banks into distinct business models and the empirical estimation model. Section 4.4 reports the empirical results, and further tests respectively, whilst Section 4.5 concludes.

4.2. Literature review and hypothesis development

The concept and recognition of business models as a "strategic choice" is rooted in the work of Hunt (1972) and the strategic management literature (see Zott and Amit (2011) for a review). In the banking literature, business models represent key management strategies that translate into several balance sheet and income statement ratios (see e.g., Mergaerts and Vander Vennet, 2016). The literature has adopted more systematic quantitative approaches to identify and examine bank business models. While some studies have focused on the linking a bank's revenue mix to profitability (see Stiroh and Rumble, 2006; Köhler, 2015), others focused exclusively on balance sheet composition (i.e., ratios) to identify bank business models (see Roengpitya et al., 2017). The choice of balance sheet composition is more directly and soundly linked to banks' strategic choices rather than income composition. Further, a bank's management is argued to have close control over the types of exposures and thus, the balance sheet of the institution (Roengpitya et al., 2017). In contrast, bank income may fluctuate over time due to systemic factors even if the overall strategy of the bank remains unchanged. Indeed, there will be parity between the revenue and profit mix and the bank's balance sheet choices over the long term (where bank business strategy remains unchanged). Nonetheless, the year-to-year differences may signal a host of factors that are beyond management's control, such as the strategy execution risks and cyclical factors attributable to the economic and financial environment.

Extant studies have examined the impact of bank business model characteristics on bank risk (Altunbas et al., 2011; Köhler, 2015), capital (Wheelock and Wilson, 2000), performance/efficiency (Mergaerts and Vander Vennet, 2016), interest margins (van Ewijk and Arnold, 2014), funding sources (Demirgüc-Kunt and Huizinga, 2010), securitization and links with financial markets (Beccalli et al., 2015), corporate governance (Laeven and Levine, 2009), diversification (Stiroh, 2010; Curi et al., 2015) and systemic risk (van Oordt and Zhou, 2019). However, little is known on how bank's earnings opacity varies with bank's business model. This is particularly important given the recent relevance of business model choice (see e.g., Roengpitya et al., 2014; Boot and Ratnovski, 2016) and its role during the recent financial crisis (Altunbas et al., 2011; Ayadi et al., 2011; Hryckiewicz and Kozłowski, 2017).

A bank's choice of business model signals its risk-taking propensity and thus, can be linked to the bank's prudence in earnings management practices. In the banking sector, earnings opacity decreases bank stability, market valuation of banks, and bank loan quality (Beatty and Liao, 2014; Bushman and Williams, 2015). Earnings manipulations also undermines internal governance and regulatory requirements such as capital adequacy violations (Jiang et al., 2016). Bank earnings opacity arises due to several reasons. First, bank managers may manipulate earnings by smoothening income to primarily safeguard their jobs (Jin et al., 2018). Kanagaretnam et al. (2003) showed that poor (good) performing managers often borrow (save) income for the future by increasing (decreasing) current income through loan loss provisions. Secondly, bank managers may also manipulate earnings so as to meet their regulatory capital or buffer requirements (Barth et al., 2017). Thirdly, where the cost of financing is dependent on a bank's perceived risk-taking, managers manipulate earnings so as to decrease their cost of borrowing. Under this scenario, management and shareholders may gain if the bank is able to secure funding on more favourable conditions (Kanagaretnam et al., 2003). Fourth, the signalling hypothesis suggests that bank managers manipulate earnings in order to signal private information about future prospects (Huang and Ratnovski, 2011). Fifth, listing status may also affect bank earnings opacity/management given that public and private firms have varying degrees of information asymmetry and long-run investor proportions (Beatty et al., 2002). Lastly, high-quality audit may restrict earnings opacity/management particularly where auditors have better expertise and greater independence (Kanagaretnam et al., 2010). Collectively, these managerial self-serving biases may mislead shareholders about the banks underlying performance/value, and/or affect contractual positions (Cheng and Warfield, 2005; Bergstresser and Philippon, 2006). Accordingly, the agency theory postulates that the board of directors have the primary mandate to effectively monitor bank managers in order to mitigate managerial opportunistic discretions in financial statements and enhance transparency in disclosures (Park and Shin, 2004; Fan et al., 2019). I use two alternative approaches to capture the permanence and the scope of business model strategies. The first approach uses individual bank characteristics to directly explain earnings opacity. The second approach employs the factor analysis to determine key factors that capture the inherent latent strategies of business models. Therefore, the research hypotheses discussed are driven by the first approach (and to some extent the second approach) where business model features captured using a set of variables that reflect the banking institution's strategic choice via its asset, liability, capital, and income structure.

4.2.1 Liability (funding) structure and bank earnings opacity

Two opposing arguments underpin the link between bank funding structure (retail-oriented vs wholesale business model) and earnings opacity. First, a business model that supports greater reliance on retail deposits is positively related to bank's earnings opacity. This outcome is particularly so where retail depositors have less information on bank or managerial conduct either because the depositors have fewer incentives and/or resources to ensure effective monitoring and discipline of bank/management conduct (Calomiris and Kahn, 1991). The weaker incentives to monitor managers and bank risk-taking may also arise where retail depositors are insured by explicit government deposit schemes that ensure that depositors bear a lower risk of losing their deposits. Accordingly, Martinez Peria and Schmukler (2001) argue that uninsured depositors enforce stringent monitoring mechanisms because they may suffer greater losses during bank failures. Furthermore, retail depositors may lack the financial expertise needed for gathering and/or processing financial information accurately (Calomiris and Kahn, 1991; Demirguc-Kunt and Huizinga, 2010), and thus render depositors ineffective at monitoring banks/management. Consequently, banks that rely heavily on retail deposits may often supply low-quality accounting information to retail depositors. Furthermore, retail-oriented banks characterised by highly volatile earnings have high probability of engaging in income smoothing and earnings management activities (Jin et al., 2018).

In contrast, a business model that emphasizes greater reliance on retail deposits may be negatively related to earnings opacity. Given that deposit insurance schemes fail to sufficiently cover all retail deposits, depositors may develop incentives to either monitor bank behaviour/operations personally or pressure authorities to do so. For instance, with retail depositors reacting adversely to non-financial information, US banks that provided financing for the much-disputed Dakota Access Pipeline recorded significant declines in retail deposits, particularly for branches that are very proximate to the site (Homanen, 2018). In recent years, negative retail depositor reaction to bank scandals is a widespread phenomenon (see e.g., Hasan et al., 2013; Berger and Turk-Ariss, 2015). More importantly, retail deposits represent a highly stable source of bank funding (Gatev and Strahan, 2006; Song and Thakor, 2007) since retail depositors incur greater turnover costs to switch banks (Kim et al., 2003). Also, the presence of deposit insurance schemes discourages retail depositors from switching amongst banks against wholesale financiers who provide funding on a short-term (usually daily) rollover basis, and that are highly susceptible to market-wide liquidity shocks (Dagher and Kazimov, 2015). Thus, given that retail depositors are highly stable and less sensitive to information relative to other counterparts, retail bank managers will have less incentives to manipulate accounting information (Forti and Schiozer, 2015). Retail-oriented banks also tend to foster better customer/depositor relationships and thus, enabling depositors to effectively assess their inherent risks (Loutskina and Strahan, 2011). Specifically, these lending relationships that develop from "soft" data (e.g., personal connections, reputation etc.) incentivise bank managers to divulge high-quality, private or sensitive financial information and disclosures to key depositors, and consequently decreases information asymmetry between banks and retail depositors (Allen et al., 2004; Puri and Rocholl, 2008). Accordingly, I argue that because reliance on retail depositors facilitate stronger lending relationship and funding stability, banks that depend significantly on retail deposits should have a lesser tendency to engage in earnings management. Simply, retail-oriented banks should have less challenges in rolling over the funds required to achieve their earnings and cash flow targets. Grounded on the above counter arguments regarding the impact of retail-oriented bank business model on earnings opacity, the following hypotheses are stipulated:

Hypothesis 1A: Retail-oriented bank business models will stimulate earnings management practices.

Hypothesis 1B: Retail-oriented bank business models will mitigate earnings management practices.

In the context of wholesale funding, depositors may also be ineffective at monitoring banks or enforcing financial reporting discipline. Accordingly, wholesale-oriented business models may stimulate higher earnings opacity. This is in line with the argument that although financial market investors are highly sophisticated, and thus expected to ensure greater market discipline (Calomiris and Kahn, 1991), the level of sophistication of wholesale financiers may not sufficiently mitigate bank earnings opacity. This may be due to the presence of cognitive biases that inhibit depositors/investors from accurately deducing underlining problems in bank financial information (Iyer et al., 2016). These depositors may therefore continue to roll over their debt funding to banking institutions without envisaging any underlining bank troubles and/or failures (Gallemore, 2013). Furthermore, certain categories of wholesale lending are less risky or safer to depositors/lenders although they may be unsecured. For instance, a repurchase agreement (repo) employed in secured wholesale lending transactions mandates that where a borrowing bank defaults, the depositors/lenders can nullify the agreement and either retain or trade the collateral which is inherently more valuable than the repo deposit (Gorton and Metrick, 2012). This guarantee to recover incurred losses discourages repo lenders from monitoring banks effectively through a complex process of financial report auditing. Besides, even where wholesale transactions are unsecured, lenders may have little motivations to undertake the complex bank financial report examinations and instead react to negative public signals by withdrawing their funds, and consequently causing bank liquidations (Huang and Ratnovski, 2011).

Furthermore, the debt covenant hypothesis postulates that bank managers may manipulate accounting information and financial disclosures so as to mitigate potential covenant violations (Jin et al., 2018). Specifically, because retail deposits scarcely use covenants, retail-oriented banks have weak incentives towards pleasing their depositors via manipulation of accounting information and financial disclosures. On the contrary, certain categories of wholesale funds (e.g., subordinated debt contracts) necessitate very strict covenants which consequently create additional platforms for managers to manipulate financial information (Goyal, 2005). Moreover, the recent financial crisis highlighted the "dark side" of heavy reliance on wholesale funding which consequently triggered the liquidation of banks such as Northern Rock following sudden withdrawals due to negative public signals.

Inherently, a business model that emphasizes wholesale funding stimulates rapid expansion by mitigating the constraints imposed by local or retail deposit supply.

Demirguc-Kunt and Huizinga (2010) argue that wholesale-oriented business models are operated by larger and fast-growing financial institutions. By operating wholesale-oriented business models, these banks can proactively exploit valuable investment opportunities (Huang and Ratnovski, 2011). Nevertheless, wholesale-oriented business models may also impact the risk propensity of banks. For instance, wholesale-oriented business models affect the return on bank assets, increase financial fragility (distance-to-default) and bank stock return volatility (Demirguc-Kunt and Huizinga, 2010). Likewise, bank income volatility increases with greater non-deposit funding (Kohler, 2015). In another breadth, reliance on wholesale-oriented business models affects managerial incentives of banks. Collectively, as bank earnings volatility increases, wholesale-oriented banks would have greater incentives to manipulate accounting information and financial disclosures through earnings smoothening.

Hypothesis 1C: Wholesale-oriented bank business models will stimulate earnings management practices.

4.2.2. Income structure (diversification) and bank earnings opacity

Studies that examine the impact of diversification on bank earnings opacity are very scanty. The deregulation and financial innovation of the financial/banking sector in the past few decades reduced bank constraints while enabling them to expand operations into highly volatile and complex non-bank activities (Fosu et al., 2018). The expansion of operations amplified the complexity of bank balance sheets as well as information asymmetry of diversified banks (Stiroh, 2010; Tran et al., 2019). However, it is not clear whether the greater dependence on non-interest income affects bank earnings opacity. The link between a diversified business model and bank earnings opacity can also be examined based on two counter arguments. The agency theory suggests that the incentive for bank mangers to manipulate earnings may be aggravated through diversification (Jensen, 1986). The increasing tendency towards greater diversification in bank income streams and the expansion of non-interest income revenues usually necessitates large boards capable of overseeing/monitoring the bank's extensive operations, but their presence of which increases agency costs and allows executives to accumulate private benefits (Tran et al., 2019). Specifically, diversification increases agency conflicts between top-level executives and divisional managers, and between opportunistic managers and shareholders (Demsetz and Strahan, 1997). Top-level executives at diversified banks may lack adequate knowledge of each division, and divisional managers may have private information or expertise specific to certain spheres of operations. The mismatch between their incentives drives greater agency costs (Xie et al., 2003).

Given the complex nature of current bank business, board members with diverse expertise are required to ensure effective monitoring, advisory and disciplining of operations. Although larger bank board presence offers valuable gains, it may exacerbate board-shareholders and board-management agency costs. For instance, large bank boards are found to be poor at monitoring management and may consequently incentivise bank managers to accumulate private wealth (Park and Shin, 2004). Simply, operating a diversified business model when the board is incapable of effectively monitoring, advising or compensating executives intensifies opportunities for managerial self-serving behaviours such as bank managers favouring decisions that grants them more power and prestige (Chen et al., 2011), increases their compensation (Chhaochharia and Grinstein, 2009), or mitigates their idiosyncratic risk (Pathan, 2009). An enthusiastic bank manager may also champion diversification or entry into new or profitable activities, and consequently increase information asymmetry between a bank and its stakeholders (Lim et al., 2008; Rodríguez-Perez and van Hemmen 2010). Collectively, operating a diversified business model should therefore stimulate bank managers to manipulate accounting information and financial disclosures through earnings smoothening particularly where the board is incapable of effectively monitoring or incentivising managers.

In contrast, a counter argument suggests that operating a diversified business model should rather mitigate asymmetric information in banks. Under the monitoring hypothesis, although diversification is associated with greater complexity and bank size, it may also stimulate greater scrutiny or pressure from supervisory authorities, regulators, financial analysts, rating agencies, amongst others (Acharya et al., 2006). Given their significant industry knowledge and communications with executives, these authorities can gather new information about a bank's operations. As such, they may publish their fears about a bank's inherent performance/value via research reports, recommendations, or ratings towards enhancing the strategic decisions of investors/funders (Yu, 2008).

Where bank managers anticipate that these information mechanisms will increase transparency requirements of their risk propensity, they are discouraged from adopting practices that would create adverse publicity with shareholders. Therefore, the monitoring hypothesis envisages that greater diversification in operations should lessen the probability of earnings manipulation since managers will face greater scrutiny/pressure from investors and other stakeholders (Jiraporn et al., 2008; Vasilescu and Millo, 2016). Given the counter arguments from the information asymmetry and the monitoring hypothesis regarding the impact of a diversified bank business model on earnings opacity, the following hypotheses are stipulated:

Hypothesis 2A: Diversified bank business models will stimulate earnings management practices.

Hypothesis 2B: Diversified bank business models will mitigate earnings management practices.

4.2.3. Capital structure and bank earnings opacity

Bank capital regulation aims at mitigating moral hazard biases associated with the implementation of deposit insurance schemes, lender-of-last resort facilities, and other forms of government guarantees (Karaoglu, 2005; Hamadi et al., 2016). For instance, because shareholders inherently have a right to the firm's assets during liquidation, their equity value increases as leverage and bank risk propensity increases. To address this moral hazard problem, regulators impose capital adequacy requirements. Accordingly, the period of increased bank deregulation was partially balanced with greater emphasis on bank capital requirements under the prudential regulatory framework, as envisaged in the initial Basel Accord on capital standards, and successive amendments (Altunbas et al., 2011). Practically, higher capital reserves boost a bank's ability to overcome sudden withdrawals or losses that arise from negative public signals. Also, government deposit insurance schemes may fail to fully insulate losses, and therefore shareholders are incentivized to maximize the option value of the deposit insurance by taking extreme risks (Karaoglu, 2005). In this context, greater capital decreases risk-shifting incentives of banks (Hamadi et al., 2016). Under moral hazard biases, bank capital structure is also linked to asset-shifting towards highly risky assets (Mehran and Thakor, 2011). Greater capital levels increase stringency when screening bank borrowers and thus, decreases bank risk (Coval and Thakor, 2005).

Attempting to optimise the capital structure via earnings management practices often affects financial reporting quality and causes extreme agency costs (Anandarajan et al., 2007). Based on monitoring dimension of the market discipline hypothesis, I expect a negative relation between capital-oriented business model and bank earnings opacity. This relation manifests because of the existence of managerial discretion on the magnitude or timing of loan loss recognition and the level of loss provisions in financial reports. Bank managers tend to smooth earnings in order to attain, improve or maintain capital adequacy levels so as to evade punishments from regulators for failure to meet minimum regulatory requirements. Particularly, banks that are close to violating minimum capital requirements or face higher costs of violating capital requirements have greater incentives to engage in earnings manipulations (Lobo and Yang, 2001). For instance, when a bank chooses to expand through mergers and acquisitions (M&As), they require regulatory approval for their transactions. Capital adequacy requirements constitute a core aspect of the M&A approval process (Valkanov and Kleimeier, 2007). Regulators usually impose higher regulatory capital requirements on banks that champion expansion through aggressive M&A. Moreover, capital requirements restrict the rapid growth of banks given that where a bank fails to meet the minimum requirements, such bank is unable to access extra deposits or investments in loans. Thus, bank managers use their discretion to manipulate earnings towards meeting regulatory capital requirements. Given that highly capitalized and liquid institutions are better equipped to withstand shocks during crisis (Demirguc-Kunt et al., 2013), I expect banks with significantly greater costs of breaching capital requirements to engage more in earnings management. Therefore, the following hypothesis is formulated:

Hypothesis 3: Capital-oriented bank business models will mitigate earnings management practices.

4.2.4. Asset structure and bank earnings opacity

Structural changes in the banking sector (e.g., deregulation and financial/technological innovation) has dramatically metamorphosed the traditional and segmented banking institutions into highly consolidated, multiple-product financial institutions (Blaško and Sinkey Jr, 2006). Commercial banks have growingly shifted their product and asset portfolios into consumer lending, conventionally a specialty of thrifts, mutual, credit unions and savings banks (Huang et al., 2012). In principle, larger financial institutions have greater incentives due to the existence of "too-big-to-fail" problems or diversification opportunities (Deng et al., 2007; Demirgüc-Kunt and Huizinga, 2010). Based on the "too-big-to-fail" hypothesis, larger banks tend to be bailed out through government assistance during crisis periods (Shim, 2013). Simply, where a bank diversifies/expands geographically via M&A to achieve a "too-big-to-fail" status, its uninsured liabilities would have de facto insurance coverage which ensures that the implicit value of government guarantees are maximised. Accordingly, I argue that size is not solely is a core determinant of bank risk-taking propensity (Huang et al., 2012) but also influences managerial behaviour for earnings management.

The loan-to-assets ratio is a key industry-specific metric that captures a distinct aspect of the asset structure. The loan-to-assets ratio indicates the extent to which a bank is involved in traditional lending activities and thus enables investors obtain a comprehensive analysis of the bank's operations (Mergaerts and Vander Vennet, 2016). Banks characterised by relatively high loan-to-assets generate a significant proportion of their income from loans and investments whilst those with low loans-to-assets rely on highly diversified, non-interest earning sources, such as asset management or trading. While the latter is associated to commercial banks because they are more active in non-lending activities, savings, mutual and cooperative banks largely focus on lending (Köhler, 2015). Moreover, these commercial banks are stock institutions funded by shareholders and investors, and are thus accountable to external parties. However, savings, mutual and cooperative banks are owned/funded by their depositors (Anandarajan et al., 2003). Also, commercial banks have greater liquidity compared to savings, mutual and cooperative banks. Given that commercial banks rely significantly on wholesale funding, they hold larger stock of liquid assets as buffer against unexpected shocks. On the other hand, savings, mutual and cooperative banks largely finance their loans with customer deposits that tend to be stickier and less susceptible to unexpected withdrawals. These distinctions in their organizational structures may have key implications for the earnings and capital management practices of bank managers. Generally, banks that are close to violating minimum capital requirements or face higher costs of violating capital requirements have greater incentives to engage in earnings manipulations (Lobo and Yang, 2001). Savings, mutual and cooperative banks have less incentives to use income smoothing strategies relative to their commercial bank counterparts who face greater scrutiny/pressure from investors, regulators and other stakeholders (Jiraporn et al., 2008; Vasilescu and Millo, 2016). Based on these arguments, commercial banks that are generally associated with lower loan-to-assets ratio and have relatively higher costs of violating capital requirements will have a greater incentive to manipulate earnings. Therefore, the following hypothesis is formulated:

Hypothesis 4A: Traditional lending business models will mitigate earnings management practices.

Prior studies also suggest that banks can use loan loss provisions to manage earnings as well as to signal private information about future opportunities (see Anandarajan et al., 2007; Leventis et al., 2011). The agency theory proposes that bank managers increase performance and managerial private benefits through the use of loan loss provisions in income smoothing (Tran et al., 2019). The rationale behind the use of loan loss provisions for earnings management is that low volatility in earnings is a core requirement for stable share pricing (Anandarajan et al., 2007). In practice, bank managers have discretion on the magnitude of loan loss provisions and realized security gains (losses) reported in any period. Therefore, during periods of low profit in other operational segments, managers can smoothen earnings by delaying or understating reported loan losses and/or increasing (decreasing) the realization of securities gains (losses) (Cornett et al., 2009). Although the monitoring hypothesis suggests that banks are constantly under the supervision and oversight of regulators, a bank's reported loan loss provisions and realized securities gains (losses) are principally under management control. Managers may use their discretion to prioritise the achievement of their private goals (e.g., increased compensation) by constantly overstating reported earnings in breach of regulatory requirements (e.g., using earnings management to overstate reported capital requirements). Based on these arguments, loan loss provisions should have a positive impact on bank earnings opacity. Therefore, the following hypothesis is formulated:

Hypothesis 4B: Business models characterised by riskier loan portfolios (e.g., discretionarily targeting less creditworthy borrowers) will stimulate earnings management practices.

Finally, the political cost hypothesis postulates that large firms tend to be very sensitive to reported earnings because they are closely monitored by financial analysts, rating agencies and investors (Alali and Jaggi, 2011). Large banks characterised by larger market capitalization tend to have extensive shareholder base, which ensures that they attract special attention from analysts, investors, and systemic risk regulators (Huang et al., 2012). Given this greater scrutiny, larger banks should be highly sensitive to stock market and focus significantly on their reported earnings. In addition, large banks have superior shock absorption capacity during violations of capital requirements as well as superior negotiation skills to deal with regulators (Jiang et al., 2016). Further, large banks have superior profitability and/or ability to generate capital internally. As such, they may not even have to raise capital in the capital market (Shrieves and Dahl 1992). Even if they do, they can raise capital relatively easily even where they fail to meet the capital requirements. Accordingly, managers of large banks will focus significantly on reported earnings rather than meeting capital requirements. Against the above backdrop, I argue that managers should have stronger incentives to manage earnings towards meeting the market expectations. Furthermore, if a “too-big-to-fail” effect does stem from diversification, managers of resultant large banks will have greater opportunities to smooth reported earnings due to the increased complexity of their firm’s operations which inhibits investors from detecting earnings manipulations (Lobo and Zhou 2006). Large banks are also associated with greater agency costs and thus implying that the firm size plays is imperative in managerial decision-making (Huang et al., 2012). In contrast, small banks may under the monitoring hypothesis have a greater incentive to meet higher capital requirements in order to avoid likely liquidations or being targeted in unfavourable takeovers during financial distress (Francis and Osborne, 2012). Based on these arguments, I expect the large banks to manage reported earnings more than the small banks. Therefore, the following hypothesis is formulated:

Hypothesis 4C: Large bank business models will stimulate earnings management practices.

4.3. Methodology

4.3.1. Data and sampling

To achieve the goal of this study, I collect financial data on individual banks from the Orbis Bank Focus database (Bureau Van Dijk) and regional data from the UK Office of National Statistics. The initial sample comprises 543 banks in the UK. To stand a chance of inclusion in the analysis, the bank must have the data necessary to estimate the opacity functions; and the data must span the period 2010 to 2018. Focusing on the period between 2010 to 2018 allows for the examination of whether bank opacity levels have decreased following the ongoing and unprecedented shift towards a highly regulated banking industry after the financial crisis. Also, in line with Mergaerts and Vander Vennet (2016), the bank's customer deposits (loans) must exceed 5% of liabilities (assets). A bank must also satisfy at least once, one or both of the two size criteria: absolute size (total assets) exceeding 5 billion dollars or systemic size (total assets to GDP) above 5%. Further, to ensure the full exploitation of the Orbis database, the collected balance sheet data comprised banks that adopt IFRS or local GAAP[18] accounting standards. A greater portion of the banks in the sample use IFRS accounting over the sample period. A relatively small proportion of banks use US GAAP in the sample but this is not surprising given that the UK banking system has an enormous domestic presence and operations of foreign banks to match the large-scale global operations of UK banks. This produces a highly homogeneous dataset (in terms of financial services) and enhances the

[18] International Financial Reporting Standards versus Generally Accepted Accounting Principles.

comparability of sampled banks in examining the business model effect on earnings opacity.

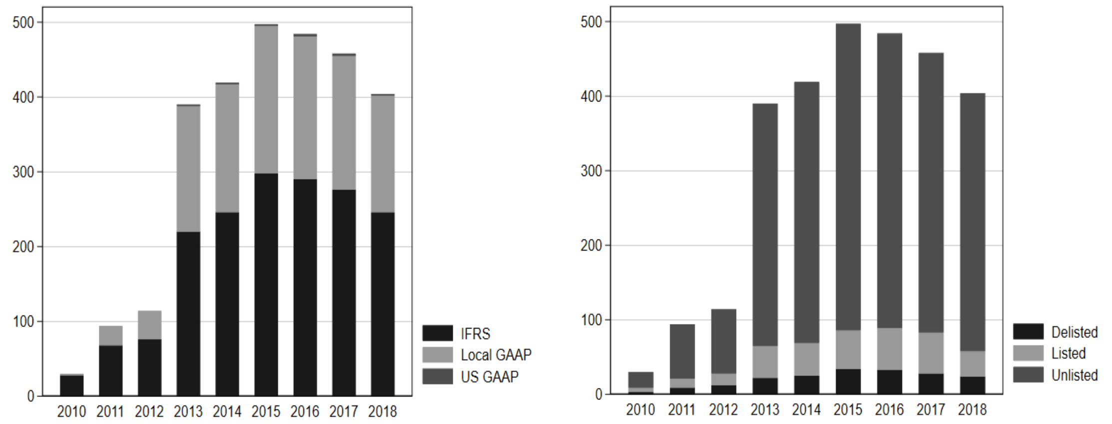
Furthermore, a banking institution is included in the sample once it is engaged in financial intermediation activity. Compared to other jurisdictions such as the US, the scope of regulations surrounding banking activities is very limited in the UK and European banking sector. Consequently, leading to the development of a banking sector that epitomises an extensive and incessant range of available intermediate strategies, stretching beyond small savings and cooperative banks, to big financial conglomerates characterized by extensive non-retail activities (Mergaerts and Vander Vennet, 2016; Handro, 2019). Therefore, a bank is included in the sample given that it is classified on Bankscope as a commercial, savings, cooperative, mortgage, governmental credit institution or a bank holding company. Banks that are not engaged in financial intermediation (e.g., investment banks) as well as banks that primarily oversee the wholesale activities of their parent groups are excluded from the analysis. Likewise, following Köhler (2015), the sample consists of both listed and unlisted institutions to control for the diverse nature of these banking specializations given that most savings institutions are unlisted. Therefore, the final sample consists of 137 banks with 1233 bank-year observations representing a greater share of the UK banking sector. Table 4.1 reports the criteria for selection of sampled banks. In Figure 4.1, I report the composition of the sample over the period of analysis based on whether they adopt the IFRS or GAAP, and whether or not they are listed or not.

Table 4.1: Summary of sampling criteria

	Condition	**Where condition is not satisfied, delete:**
1	Customer deposits exceed 5% of liabilities	Bank-year observation
2	Loans exceed 5% of assets	Bank-year observation
3	Earnings opacity data are fully available	Bank-year observation
4	Income data are fully available	Bank-year observation
5	Availability of continuous bank data (i.e., no gaps)	All bank observations prior to gap

The table reports the criteria for selection of sampled banks.

Figure 4.1: Composition of sample by accounting standards, listing status, and years.



4.3.2. Estimation method

To achieve the aim of examining business models as both short- and long-term concepts, the disparities "within" and "across" banks are vital towards identifying the effect of business models on earnings opacity. Accordingly, I identify business model effects using both the "between" and "within" dimension (i.e., between banks and within banks over time). Specifically, it is vital to examine performance differences both within and between banks that have distinct deposit ratios, rather than solely examining the performance impact arising from a change in the ratio within one bank. The choice and interpretation of the within versus between effects to capture short- vs. long-term effects and consequently business model effects is buttressed by econometric literature on panel analysis. For instance, by estimating the long-run effects directly from a static model, the between estimator mitigates any dynamic misspecifications (Mundlak, 1978; Pirotte, 1999). Accordingly, I relied on the approach proposed by Mundlak (1978) to simultaneously explore both the within and between dimension of the model. The approach uses the random effects estimation where the individual means of the predictors serve as regressors. This mitigates any biases that arise due to correlation between the predictors and unobserved effects (Mergaerts and Vander Vennet, 2016). Research advocates for the use of within estimators and bank fixed effects to mitigate distinctions between banks that may not have direct link to the business model, but may impact the observed bank characteristics, such as risk culture or preferences (Fahlenbrach et al., 2012; Köhler, 2015). Nevertheless, though the Mundlak model is inadequate for decomposing the individual variables into those that directly relate to the business model versus those that reflect other resolute disparities, Altunbas et al. (2011) argues that all these disparities (e.g., risk culture or preference) constitute the bank business model. In the second stage analysis, the factor approach however enables a distinction between those variables that are related to the business model. Additionally, a residual variation component is estimated to capture incessant bank-specific disparities that also impact the bank characteristics. Specifically, the common factors enable the decomposition of the bank fixed effects into a business model component and a residual component.

Grounded on the above, I use two alternative approaches to capture the permanence and the scope of business model strategies. In the first approach, I the use of individual bank characteristics to directly explain earnings opacity. The second approach employs the factor analysis to determine key factors that capture the inherent latent strategies of business models. Specifically, I specify the following baseline via the Mundlak estimator:

$$EO_{i,t} = \beta X'_{i,t} + \gamma \bar{X}'_{i} + \delta_t + \alpha_i + \varepsilon_{i,t} \tag{4.1}$$

where EO_{ict} represents the earnings opacity of bank *i* in year *t*. X' is the vector of all predictor variables (business model and bank-specific control variables), and $\bar{X}'$ denotes the individual means of the predictor variables across the entire sample period. To account for endogeneity, I utilise the first lag of the independent bank-specific variables, $X'_{i,t}$. Additionally, I incorporate a bank-year fixed effect, δ_t, to account for differences in the macroeconomic or banking environment given that these conditions may propel variations in strategic outcomes for similarly classified banks. The within and between parameters, denoted by $\hat{\beta}$ and $(\hat{\beta} + \hat{\gamma})$ respectively, are directly reported in the results section. The specified baseline model also controls for unobserved heterogeneity and correlation between unobserved effects, α_i and the predictors, $X'_{i,t}$, whilst also accounting for any cross-sectional dispersions in the data. Additionally, the specification enables an intuitively clear interpretation of the within (i.e., the effect of changes over time within banks) versus between effects (long-run business model effects).

4.3.3. Identification of bank business models

Bank business models can be identified through the direct or indirect approach. The direct approach uses qualitative variables, such as Orbis "bank type" to identify business models (Köhler, 2015). The indirect approach uses the cluster analysis to combine information on single assets or liability transactions (Roengpitya et al., 2014). Nevertheless, these approaches have been criticised for their failure to capture the nature of the entire banking asset structure and scale of different bank activities. Specifically, the assumption of an existence of inherently distinct business models and thus, the absence of intermediate strategies. These approaches also ignore from their analyses, the correlation both within and between bank asset and liability structures (Hryckiewicz and Kozłowski, 2017). In the European banking sector, the scope of regulations surrounding banking activities is very limited relative to the US where these studies where undertaken. For instance, the recent unprecedented consolidation trend in Europe and UK has led to the development of a banking sector that epitomises an extensive and incessant range of available intermediate strategies, stretching beyond small savings and cooperative banks, to big financial conglomerates characterized by extensive non-retail activities (Mergaerts and Vander Vennet, 2016; Handro, 2019).

Alternatively, the banking literature (e.g., Demirgüc-Kunt and Huizinga, 2010; Altunbas et al., 2011) propose the use of approaches that attempt to directly capture bank-specific business model characteristics. This chapter adopts such approach, given that it enables the identification of bank-specific business model features that may enhance performance. Nevertheless, the approach is criticised for its inability to fully capture the "business model effect", because it fails to clearly explain the interconnections between the specific characteristics that constitute a business model (Mergaerts and Vander Vennet, 2016). Moreover, it fails to also account for independent bank-level variations in the business model variables that are not due to the chosen business model strategy. For instance, higher bank capital ratio may signify the institution's chosen business model given that it is linked to the institution's funding strategy, yet this may similarly indicate the risk-taking propensity of the banking institution (Teece, 2010). Specifically, banks may adopt a persistent and aggressive "risk culture" that may consequently have long-term implications on the bank-specific characteristics (Fahlenbrach et al., 2012).

Grounded on the above, this chapter follows Mergaerts and Vander Vennet (2016) and uses the factor analysis to identify bank business models. This approach regards a business model as an underlying, latent strategy. Specifically, the observed strategic variables are the outcome of the chosen strategy, but also of bank-specific variation. The factor approach utilises the common variations in the business model factors to capture latent strategies. Similar to the clustering approach, it integrates information from all variables and observations. However, rather than generating binary groupings, it produces continuous common factors. Inherently, common factors are more precisely estimated for variables that have more variation in common (Boivin and Ng, 2006), which in this case, more clearly defines the business model. Therefore, the factor approach captures the extent to which variables constitute the underlying strategy and uniqueness or specificity in the extent of their variations.

4.3.4. Business model variables

This study captures business model features using a set of variables that reflect the banking institution's strategic choice via its asset, liability, capital, and income structure.

Asset structure focuses on value preposition usually through the provision of financial and advisory services, and/or selling financial products, such as loans and securities (Osterwalder and Pigneur, 2010). I capture the value preposition via three measures. First, the ratio of net loans to earning assets (LOAN) measures the degree of involvement in conventional intermediary activities. Specifically, how liquid deposits are transformed into illiquid loans, which collectively signal the core role of delegated monitoring (Mergaerts and Vander Vennet, 2016). Second, the ratio of Loan loss provisions (LLP) to loans is employed to capture asset quality and reflects the bank's discretion on the quality of its loans (i.e., assets). The LLP, though, may be utilised to smoothen income as well as manipulated by forbearance, particularly during crisis periods (Laeven and Majnoni, 2003). Third, bank size (SIZE), measured as the natural log of total assets, is used to capture the effects of diversification, and economies of scale and scope (e.g., access to markets). Nevertheless, larger banks may become "too-big-to-fail", or too complex to manage. Additionally, in the presence of greater capital market inefficiencies, they may suffer greater losses and therefore become riskier (Altunbas et al., 2011).

Liability structure focuses on the structure of on-balance sheet and short-term wholesale funding (Altunbas et al., 2011). I use the ratio of deposits to liabilities (DEPO) to capture the dependence on traditional customer or retail deposits. Additionally, I capture any reliance on short-term wholesale funding via the ratio of short-term marketable securities to total assets (STMKT), which might make banks more exposed to funding liquidity shocks. Retail deposits tend to provide more funding stability relative to wholesale markets due to the existence of government deposit guarantees. Therefore, banks that have broader deposit base may possess synergistic advantages in their lending activities and be more resilient during crisis or stress periods (Gatev et al., 2009; Mergaerts and Vander Vennet, 2016). Similarly, banks may adjust their balance sheets swiftly by relying on relatively cheap and abundant short-term wholesale funds. Accordingly, I use the net stable funding ratio (NSFR) to capture any risk associated with the bank's funding strategy that stems from maturity mismatch between the liquidity of assets and liabilities. A higher NSFR implies stronger structural liquidity (low levels of funding risk). I compute the NSFR following the Basel III regulatory framework (BCBS, 2017) as:

$$NSFR = \frac{Available\ stable\ funding}{Required\ stable\ funding}$$

$$= \frac{Equity + Liabs_{>1yr} + \left(StableDeposits_{<1yr} * 95\%\right) + (OtherDeposits * 90\%) + (StDebt * 50\%)}{(GovtDebt * 5\%) + \left(CorpLoans_{<1yr} * 50\%\right) + (Mtgs * 65\%) + \left(RetLoans_{<1yr} * 85\%\right) + (Other * 100\%)}$$

Income structure focuses on the degree of income diversification and the extent to which a bank has shifted towards more volatile noninterest income (Altunbas et al., 2011). The measurement of non-interest income is criticised for inherent weakness during the recent crisis, when the level fell significantly in several banks to the extent that some banks even recorded negative values. To mitigate this challenge, I follow Mergaerts and Vander Vennet (2016) to replace all negative values of non-interest income with zero given that negative income diversification ratios lack clear economic interpretation.

Capital structure gives insights into a bank's risk attitude, leverage and loss-absorbing. For banks, equity capital is more costly relative to debt capital and thus increase in cost of capital is passed on to their loan customers via higher interest rates. I use capital ratio (CAP), measured as the ratio of equity to total assets, to capture the bank's ability to use its available equity to absorb losses. To account for high-quality (i.e., core) equity, I also use the ratio of Tier I capital to total assets. Although Tier I capital still serves as a more effective tool towards safeguarding a bank's financial viability (Demirguc-Kunt et al., 2013), risk weighting for both unweighted and regulatory ratios have declined in the past few years due to the strategic use of internal risk models by banks (Mariathasan and Merrouche, 2014). Moreover, bank capital has an ambiguous effect[19] on risk propensity and distress. Accordingly, I follow the Basel committee proposal (BCBS, 2017) and Altunbas et al. (2011) to interact the Tier I capital ratio with a high capital indicator[20] (CAP_eta) to capture any non-linear effect of bank capital on bank risk, and therefore earnings opacity.

4.3.5. Earnings Opacity

To measure bank earnings opacity, I follow existing research (e.g., Jiang et al., 2016; Jin et al., 2018) to use the magnitude of discretionary loan loss provisions (DLLP). LLPs are core components of bank expenses and accruals. They signal information asymmetry because they rely on the managers' discretion of the banks' loss absorption capacity (Cohen et al., 2014). Practically, financial institutions may smoothen earnings through loss provisioning towards achieving opportunistic goals (Jiang et al., 2016). I adopt the Beatty and Liao (2014) approach to model discretionary provisions. The approach allows the separation of the normal (non-discretionary) component of LLP, which is due to changes in the fundamentals of performance, from the abnormal (or discretionary) component which may be attributable to managerial discretion. The abnormal component serves as the proxy of bank earnings opacity. Specifically, I estimate the following OLS regressions of LLP:

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[19] Capital reduces the likelihood of bank distress where capital acts as an ex-ante buffer against potential losses. Conversely, capital stimulates bank distress where mandated regulatory or market agents impose strict capital requirements on riskier banks.
[20] An indicator of 1 for banks with Tier I ratio above 6% and 0 otherwise).

$$LLP_{i,t} = \beta_0 + \beta_1 \Delta NPL_{i,t+1} + \beta_2 \Delta NPL_{i,t} + \beta_3 \Delta NPL_{i,t-1} + \beta_4 \Delta NPL_{i,t-2} + \beta_5 Size_{i,t} + \beta_6 \Delta Loan_{i,t} + \beta_7 \Delta Reg\_GVA_{i,t} + \beta_8 \Delta Reg\_GDHI_{i,t} + \beta_9 \Delta Reg\_HPI_{i,t} + \beta_{10} \Delta Reg\_UR_{i,t} + Reg\_Dummy + Year\_Dummy + \varepsilon_{i,t} \quad (4.2)$$

where $LLP_{i,t}$ is loan loss provisions scaled by total loans for bank *i* in year *t*, $\Delta NPL_{i,t}$ denotes the change in non-performing loans scaled by total loans, $Size_{i,t}$ is the natural logarithm of total assets, $\Delta Loan_{i,t}$ is the change in total loans scaled by total assets, $\Delta Reg\_GVA_{i,t}$ is the change in gross value added of the region where the bank is headquartered, $\Delta Reg\_GDHI_{i,t}$ is the change in gross disposable household income of the region where the bank is headquartered, $\Delta Reg\_HPI_{i,t}$ is change in the return of the house price index of the region where the bank is headquartered, $\Delta Reg\_UR_{i,t}$ is change in unemployment rate of the region where the bank is headquartered, Reg_Dummy and $Year\_Dummy$ are indicators to control for region and year fixed effects. I control for changes in NPL for four successive periods ($\Delta NPL_{i,t+1}$, $\Delta NPL_{i,t}$, $\Delta NPL_{i,t-1}$, $\Delta NPL_{i,t-2}$) given that changes in NPL will necessitate changes in LLP. Moreover, banks may utilise historical, current and forward-looking information on NPL to guide strategic LLP decisions (Jin et al., 2018). Additionally, change in loans ($\Delta Loan_{i,t}$) is included to account for changes in the quantity of loans when loan quality changes.

To corroborate my results, I also adopted a modified version of Eqn. (4.2) following Kanagaretnam et al. (2010). This model is estimated as:

$$LLP_{i,t} = \beta_0 + \beta_1 Loan_{i,t} + \beta_2 \Delta Loan_{i,t} + \beta_3 LLA_{i,t-1} + \beta_4 CO_{i,t} + \beta_5 NPL_{i,t-1} + \beta_6 \Delta NPL_{i,t} + \beta_7 CL_{i,t} + \beta_8 RL_{i,t} + \beta_9 IL_{i,t} + \beta_{10} AL_{i,t} + \beta_{11} DL_{i,t} + Reg\_Dummy + Year\_Dummy + \varepsilon_{i,t} \quad (4.3)$$

where $Loan_{i,t}$ denotes total loans scaled by total assets, $LLA_{i,t-1}$ denotes loan loss allowance scaled by total loans; $CO_{i,t}$ is loan charge-offs scaled by total loans; $NPL_{i,t-1}$ is non-performing loans scaled by total loans; $CL_{i,t}$, $RL_{i,t}$, $IL_{i,t}$, $AL_{i,t}$, $DL_{i,t}$ represent loan categories, comprising commercial and industrial loans, real estate loans, individual loans, agriculture loans, and loans to depository institutions respectively. The inclusion of the loan category controls account for changes in loan composition that have probable effects on bank risk. For instance, banks that grant more commercial and real estate loans have relatively higher LLP than those with preference for consumer loans (Kanagaretnam et al., 2010). In both Eqn. (4.2) and (4.3), DLLP is captured via the residuals ($\varepsilon_{i,t}$).

In my initial assessment, I proxy for bank earnings opacity by using the absolute value of the residuals from Eqn. (4.2) and (4.3) (ABSDLLP-A and ABSDLLP-B), the natural logarithm of DLLP [LN(DLLP-A) and LN(DLLP-B)] to mitigate the effect of outliers, and the deviation of DLLP [DEVDLLP-A and DEVDLLP-A] computed as $DLLP_{i,t} - Average\ DLLP_{i,t}\ of\ the\ industry$. Higher values of ABSDLLP-A and ABSDLLP-B indicate higher bank earnings opacity. For robustness purposes, I use alternative measures of earnings opacity (section 4.5) based on the Discretionary Realized Gains and Losses of Securities (DRGLS) (Barth et al., 2017) and Delayed Expected Loan Loss Recognition (DELR) (Fan et al., 2019). Further, I separate the DLLP based on their signs, and examine their business model effects for both income-increasing and income-decreasing DLLP, respectively.

4.3.6. Control variables

In line with banking literature, I include key bank-specific variables to account for factors that may not directly relate to the business model, yet may critically affect earnings opacity and performance. Mergaerts and Vander Vennet, (2016) argues that operational efficiency is a business model characteristic but due to the outcome of strategic choices. Moreover, European financial conglomerates, characterised by larger size and greater diversification are inherently more efficient (Vennet, 2002). I capture these features via the standard cost-income ratio, where total cost comprise all non-interest operational expense and total income measured as the sum of noninterest and net interest incomes. Further, I include controls for the financial profitability (performance) using the return on assets (ROA) and a dummy for listing to capture key disparities between listed and non-listed banks; unlisted banks prefer a more retail-oriented business model (Köhler, 2015).

4.4. Results and discussion

4.4.1. Descriptive statistics and correlations

Table 4.2 reports the descriptive statistics for all variables. All nine strategic variables have a between variation greater than the within variation. Therefore, implying greater differences across banks (long-term) relative to changes within banks over time (short-term). Furthermore, this is consistent with the position that business models are long-term concepts, and highlights the relevance of examining the cross-sectional information. Further, I construct the bivariate correlations to test the interdependence between the strategic variables. The results which are presented in Table 4.3 show that the correlations between the opacity indicators are high. Thus, indicating that these indicators capture similar construct (earnings opacity). Furthermore, there's no evidence of significant multicollinearity issues between the strategic business model variables. Overall, the results establish the interdependence between the strategic variables and therefore, their importance as determinants of bank business models.

Table 4.2: Descriptive statistics

						Standard Deviation			
Variable	Unit	Obs.	Mean	Min	Max	Within	Between	Overall	Between/Within
LN(DLLP-A)		1233	0.0175	0.0206	1.8340	0.5103	0.2051	0.5563	0.4020
ABSDL-A		1233	0.1161	0.0002	1.8331	0.5128	0.2392	0.5711	0.4663
DEVDLLP-A		1233	0.1159	-0.0080	1.7419	0.5338	0.2424	0.5927	0.4541
LN(DLLP-B)		1233	0.0488	0.0786	0.1742	0.5184	0.2067	0.5646	0.3987
ABSDL-B		1233	0.0068	0.0000	0.2100	0.0037	0.0028	0.0046	0.7568
DEVDLLP-B		1233	0.0115	-0.1613	0.1239	0.0895	0.0229	0.0915	0.2562
LOAN	%	1233	58.5289	5.0228	80.0000	9.0251	33.8098	33.8529	3.7462
LLP	%	1233	0.5034	-0.0089	0.2020	0.5264	0.7207	0.7303	1.3691
SIZE	Ln	1233	14.1985	15.4249	21.7138	2.9425	3.6080	3.0231	1.2262
DEPO	%	1233	65.6432	33.7903	99.9004	7.6687	34.0454	33.7903	4.4395
STMKT	%	1233	13.0376	21.4452	68.8538	7.2414	20.8149	21.4452	2.8745
NSF	%	1233	93.2293	28.5631	114.0000	25.5754	33.3309	28.5631	1.3032
DIVERSE	%	1233	37.7227	7.7650	82.0000	1.3067	2.9085	1.4747	2.2254
CAP	%	1233	28.4166	21.8334	100.0000	11.1617	32.7234	33.1373	2.9318
CAP_eta	%	1233	20.3000	8.8606	24.5702	6.5000	7.9400	8.8600	1.2215
ROA	%	1233	1.4805	-1.9512	2.8993	7.8357	14.2189	14.2688	1.8146
CI	%	1233	64.4655	45.6667	70.4600	42.1211	24.2855	48.2500	0.5766
LISTED		1233	0.2408	0.0000	1.0000	0.1237	0.2897	0.3106	2.3422

The table presents the summary statistics for all the bank-specific data. The sample comprises 137 banks over the period 2010–2018.

Table 4.3: Correlation matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	LN(DLLP-A)	1.00																	
2	ABSDLLP_A	0.93*	1.00																
3	DEVDLLP-A	0.83*	0.92*	1.00															
4	LN(DLLP-B)	0.91*	0.86*	0.69*	1.00														
5	ABSDLLP-B	0.91*	0.90*	0.70	0.71*	1.00													
6	DEVDLLP-B	0.86*	0.60	0.52	0.66*	0.81*	1.00												
7	LOAN	0.02	0.02	0.01	0.04	0.07*	-0.01	1.00											
8	LLP	-0.01	-0.00	0.03	-0.02	-0.03	0.01	-0.03	1.00										
9	SIZE	0.00	-0.02	-0.02	0.00	-0.18*	-0.07*	-0.04	-0.13*	1.00									
10	DEPO	0.07	0.04	0.05	0.06	0.09*	0.02	0.33*	-0.00	-0.24*	1.00								
11	STMKT	-0.09	0.29*	0.16*	0.03	0.02	0.01	0.30*	-0.01	-0.31*	-0.37*	1.00							
12	NSF	0.01	-0.01	0.01	0.02	0.04	-0.00	-0.09*	0.04	0.02	-0.08*	-0.03	1.00						
13	DIVERSE	-0.01	-0.01	0.01	-0.01	-0.00	-0.01	-0.17*	0.08*	0.01	-0.09*	-0.09	0.02	1.00					
14	CAP	-0.02	-0.02	-0.02	-0.03	0.25*	0.03	-0.07*	0.08*	-0.54*	-0.23*	-0.08	0.04	0.02	1.00				
15	CAP_eta	-0.00	0.04	0.07	-0.01	0.07	-0.03	-0.12*	0.35*	-0.33*	0.12*	0.06	-0.01	0.04	0.31*	1.00			
16	ROA	-0.00	-0.00	0.03	0.03	0.04	0.01	0.11*	0.09*	0.03	0.02	-0.02	-0.01	0.00	0.12*	-0.28*	1.00		
17	CI	0.08*	0.03	0.02	0.07*	0.03	-0.00	-0.04	0.01	-0.04	-0.01	-0.05	0.00	0.04	0.04	0.02	-0.13*	1.00	
18	LISTED	0.01	0.07	0.07	0.00	0.10*	0.00	-0.21*	0.07	-0.32*	0.02	0.40*	0.01	0.17*	0.72*	0.47*	-0.04	0.13*	1.00

The table presents the unconditional correlation coefficient between any pair of variables. * Indicates significance at 1%.

4.4.2. Factor analysis

As stated earlier, I use the factor analysis approach (Horn, 1965) as an alternative to identify bank business models. The method utilises Monte Carlo simulation to estimate, for a given set of variables, the distribution of eigenvalues associated with the factors. Any common variance is indicated by factors that have eigenvalues greater than 0. Table 4.4 reports the results of the factor analysis. To determine the number of factors that identify business models, I estimate the critical values associated with the eigenvalues via parallel analysis. I observe that five eigenvalues are significantly positive. A higher eigenvalue better explains common variation in the factor. Therefore, factors with low eigenvalues have lower likelihood of identifying core business model strategies that can be associated to the standard bank strategies. Nonetheless, an eigenvalue greater than 0 does not essentially imply that the factor is economically meaningful. The parallel analysis indicates that three factors should be retained. The three factors have eigenvalues that are greater than the critical values (average eigenvalues) in the PA column. To confirm this, Figure 4.2 shows that the dashed line for parallel analysis crosses the solid factor analysis line just upon reaching the fourth factor/component. Therefore, I focus on these three factors to describe a bank's business model[21]. Unlike Köhler (2015) and Mergaerts and Vander Vennet, (2016) who use two variables to identify business models, I use three variables with the third variable accounting for the reliance on short-term wholesale funding in the UK and Europe.

Table 4.4: Factor Analysis

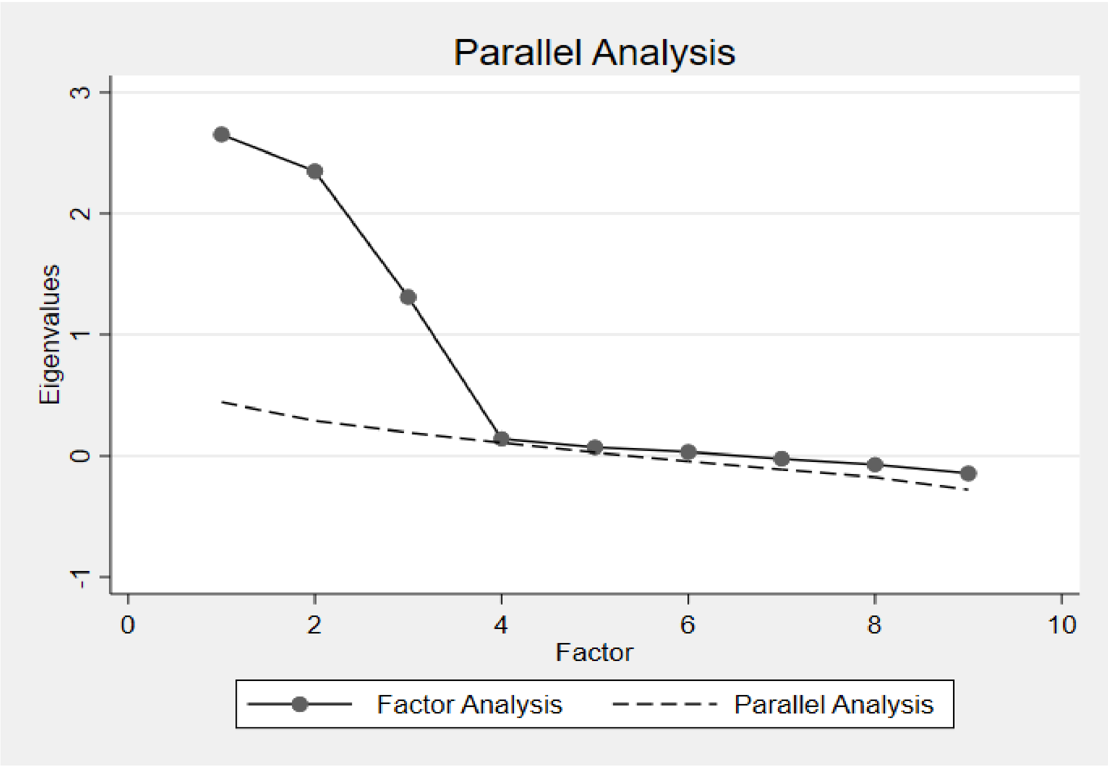
Factor	Eigenvalue	Critical Values (PA)
Factor1	2.652	0.457
Factor2	2.349	0.334
Factor3	1.310	0.218
Factor4	0.141	0.131
Factor5	0.070	0.076
Factor6	0.032	-0.064
Factor7	-0.025	-0.121
Factor8	-0.073	-0.208
Factor9	-0.145	-0.271
LR test: independent vs. saturated: $chi^2(36) = 778.58$ Prob>$chi^2 = 0.0000$		

[21] Regardless, the regression analysis includes controls for variations in bank characteristics that may not be captured by the three business model factors (the three non-retained factors) although their effects were not discussed.

PANEL B				
	Correlation with characteristics			
Variable	Factor1	Factor2	Factor3	Communality
LOAN	0.142	-0.899	0.291	0.912
LLP	0.033	0.276	-0.259	0.145
SIZE	-0.828	0.254	0.020	0.750
DEPO	0.017	-0.706	-0.235	0.554
STMKT	0.324	0.337	0.979	1.178
NSF	0.570	0.330	0.047	0.435
DIVERSE	0.070	0.824	-0.225	0.735
CAP	0.865	-0.014	-0.112	0.761
CAP_eta	0.874	-0.003	-0.279	0.841

The table reports the estimated results of the factor analysis via the iterated principal factor method (see e.g., Kim and Mueller, 1978). Panel A reports the eigenvalues of the common factors. Further, I conducted (one-sided) tests to examine whether the eigenvalues are significant using the parallel analysis (Horn, 1965). Panel B reports the correlations of the predicted factors with business model variables and the communality associated with each variable. A higher communality implies that the variable is better explained by the common factors.

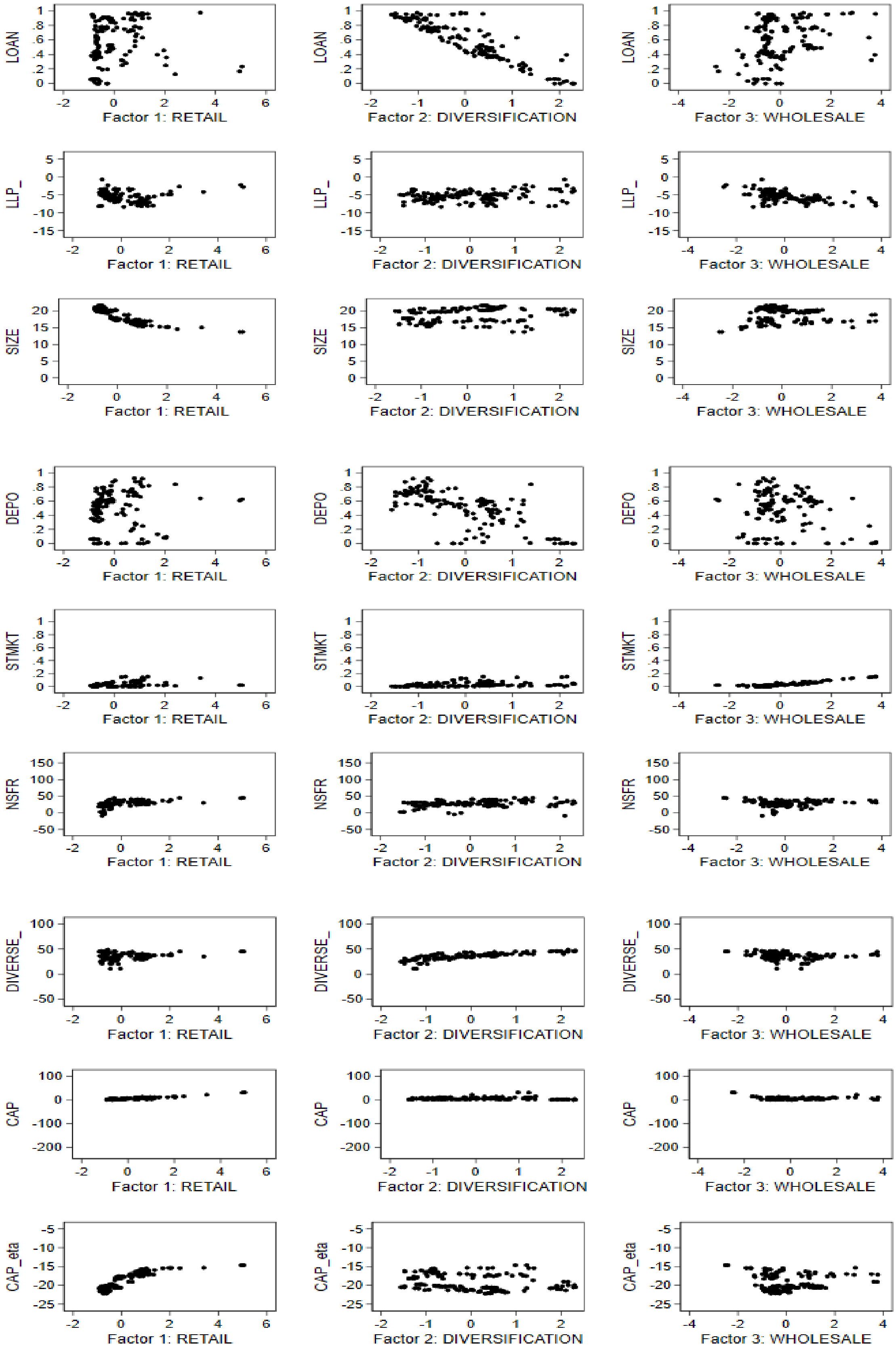
Figure 4.2: Parallel analysis for factor analysis



The parallel analysis indicates that three components should be retained. First, three of the eigenvalues in the FA column are greater than the average eigenvalues in the PA column. Secondly, the dashed line for parallel analysis in the graph crosses the solid FA line just upon reaching the fourth factor/component.

In addition, the chosen variables are closely linked to the factors in terms of interpretation. Factor 1 identifies a retail-oriented business model because it is positively related to the loan, deposit, capital and net stable funding ratios. However, it negatively relates to size and income diversification. Factor 2 identifies a diversified business model because it captures the negative relation between a high loan ratio and greater income diversification. Factor 3 identifies a wholesale-oriented business model because it captures the positive relation between high short-term marketable securities ratio and high non-retail or wholesale funding. Moreover, it negatively relates to deposits, income diversification and capital levels. Based on these correlations, I denote the three distinct factors as RETAIL, DIVERSIFICATION and WHOLESALE models respectively. Finally, the communalities in Panel B of Table 4.4 indicate that loan ratio and size, deposit, short-term marketable securities and net stable funding ratios, income diversification, and the capital ratios are best explained by the common factors. Figure 4.3 shows the graphical overview of the association between the common factors and the bank-specific business model variables.

Figure 4.3: Linking the common factors (x-axis) to business model variables (y-axis)

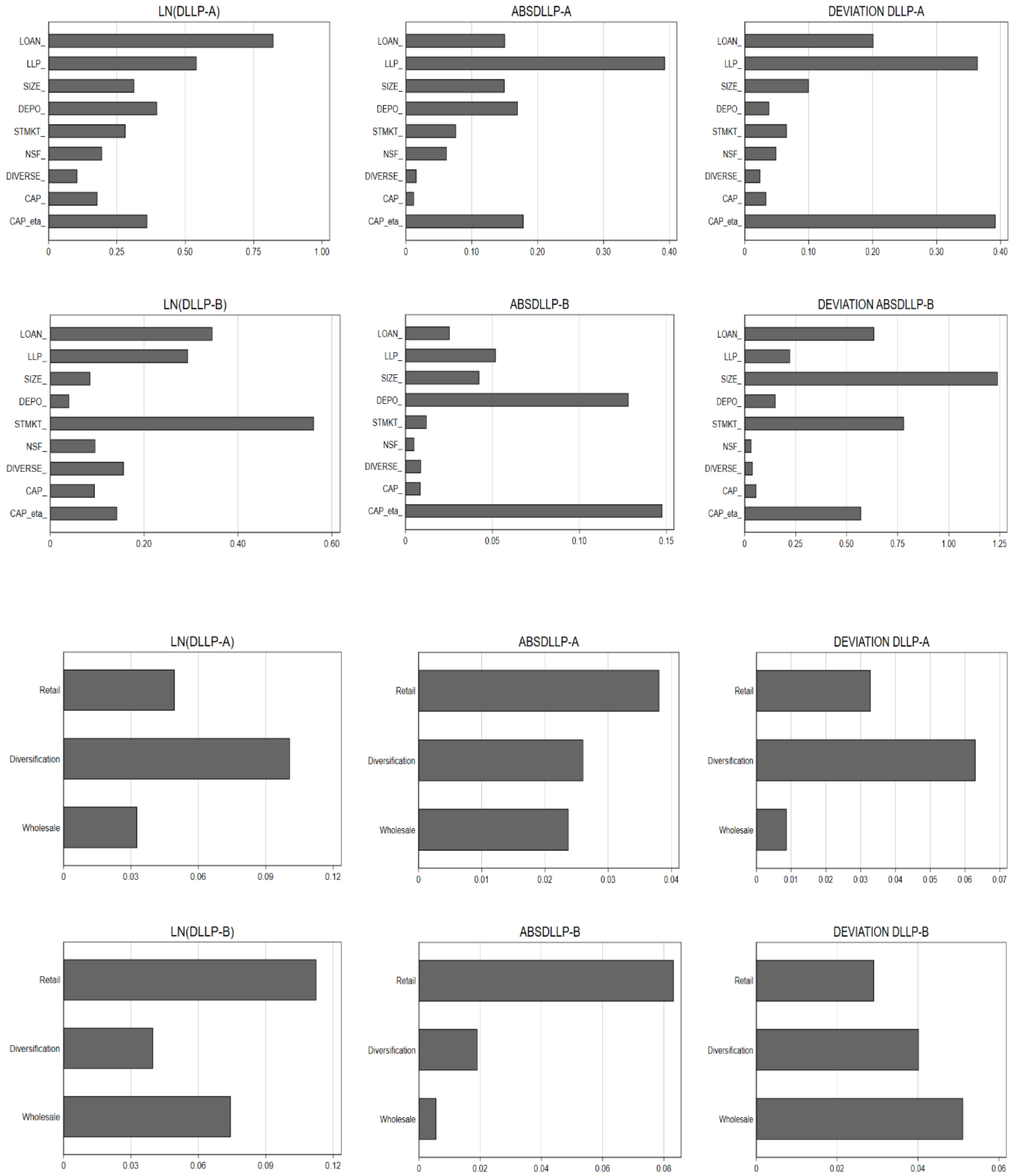


Abbreviations are as follows: loans to earning assets (LOAN), loan loss provisions (LLP), natural logarithm of total assets (SIZE), deposits to liabilities (DEP), short-term marketable securities to total assets (STMKT), net stable funding ratio (NSFR), income diversification (DIVERSE), equity to total assets (CAP), and (CAP_eta).

4.4.3. Impact of individual bank characteristics

The estimated results based on the individual business model characteristics are reported in Table 4.5. The upper (lower) panel of each Table reports the within -short-term (between -long-term) business model effects. First, the model shows a very good fit for the data. However, the R^2 statistics indicates that the model better explain the "between" relative to "within" business model effects on earnings opacity. Furthermore, I observe that several of the between effects are statistically significant both jointly and individually. A key implication of these findings is that business models are long-term strategic choices that are crucial towards explaining bank earnings opacity. The subsequent sections explore the effects of each business model strategy on earnings opacity. To ensure a more accurate judgement and comparison of the economic significance of these effects, I also compute the effect of a one (between) standard deviation change in the business model variables. The results are reported in Figure 4.4.

Figure 4.4: Absolute between effects on bank earnings opacity.



Note: A one (between) standard deviation change of the business model variables. Abbreviations are as follows: loans to earning assets (LOAN), loan loss provisions (LLP), natural logarithm of total assets (SIZE), deposits to liabilities (DEP), short-term marketable securities to total assets (STMKT), net stable funding ratio (NSFR), income diversification (DIVERSE), equity to total assets (CAP), and (CAP_eta).

4.4.3.1. Asset structure

Table 4.5 shows that while a negative impact is observed for loan ratio in the short-run (within), it is positively related to earnings opacity in the long-run (between). This effect is also economically significant and may therefore suggest that although traditional lending banks are less likely to manipulate earning in the short-term (Hypothesis 4A), they are unable to overcome this temptation in the long-term. Accordingly, in attempting to just meet or beat prior year's earnings towards meeting long-term objectives, typical lending banks may engage in greater earnings management relative to those with alternative asset structures. In the long-run, traditional banks are also subjected to greater scrutiny/pressure from investors, regulators and other stakeholders and thus, have greater incentives to use income smoothing strategies.

In terms of asset quality (LLP), a negative impact is observed in the short-term while a positive and statistically significant impact on earnings opacity is recorded in the long-term. Thus, bank business models characterized by riskier loan portfolios may stimulate earnings management in the long-term. Possible explanation for this outcome is that while a strategy that targets less creditworthy borrowers can stimulate higher net interest margins both during the short- and long-term, it reduces overall bank profitability in the long-term (Mergaerts and Vander Vennet, 2016). This is particularly true where asset quality measures can be manipulated through managerial discretion such that during periods of low profit, managers can smoothen earnings by delaying their recognition or understating their reported values towards achieving their private goals (e.g., increased compensation) (Tran et al., 2019). Banks that strategically focus on risky lending or forcibly disintermediates towards targeting more risky loan segments can feasibly pursue this goal only when managers succeed in reducing impairments by developing long-term capabilities that champion effective screening and monitoring.

Lastly, bank business models that are characterized by large size (SIZE) supports long-term earnings opacity; it has significantly positive impact on the opacity measures (Hypothesis 4C). Short-term changes to bank size, however, have a negative effect on earnings opacity: the impact on the opacity indicators is significantly negative. This suggests that although business models characterized by large size have greater long-term stability (Köhler, 2015), they are also associated with greater cost due to their risk-propensity and systemic importance (Pagano et al., 2014). In the long-run, if a "too-big-to-fail" effect does arise from diversification, managers of resultant large banks will have greater opportunities to smoothen reported earnings due to the increased complexity of their firm's operations. Accordingly, increasing bank size and complexity may thus not be a desirable channel towards achieving increased earnings transparency, which is in line with research on the causes of the recent financial crisis.

4.4.3.2. Liability structure

Under funding structure, retail funding may stimulate earnings opacity where retail depositors lack information on bank or managerial conduct due to information asymmetry and/or the resources to ensure effective monitoring and discipline of bank/management conduct (Hypothesis 1A). However, recent studies suggest that while the institution of explicit government deposit schemes lessen the risk of losing depositor's funds, the fact that these schemes fail to sufficiently cover all retail deposits stimulate depositor's incentives to either monitor bank behaviour/operations personally or pressure authorities to do so (Martinez Peria and Schmukler, 2001; Jin et al., 2018). More importantly, retail funding provides greater funding stability since retail depositors incur greater turnover costs to switch banks (Kim et al., 2003). Consistent with these findings, my results show that banks that adopt the more traditional funding structure (DEP) are transparent and engage in less earnings management both in the short- and long-run. Consistent with Hypothesis 1B, retail-oriented banks tend to foster better customer/depositor relationships that incentivise bank managers to divulge high-quality, private or sensitive financial information and disclosures to key depositors, and consequently decreases information asymmetry between banks and retail depositors (Puri and Rocholl, 2008). Accordingly, banks characterised by greater reliance on retail deposits have less challenges in rolling over the funds required to generate expected earnings and cash flows and thus, a lower propensity to engage in earnings management.

In the context of wholesale funding, the use of short-term marketable securities (STMKT) increases the probability of earnings manipulation. This is evidenced by the positive and significant impact under both the within and between analysis. In the short run, institutions that rely heavily on market funding have greater exposure to liquidity risk, particularly during crisis periods, as they face difficulties in rolling over short-term debt to finance illiquid assets. Moreover, certain categories of wholesale funds (e.g., subordinated debt contracts) necessitate very strict covenants which consequently create additional incentives for managers to manipulate financial information. In the long run, wholesale funding stimulates rapid expansion by mitigating the constraints imposed by local or retail deposit supply. Accordingly, wholesale-oriented business models are operated by larger and fast-growing financial institutions (Demirguc-Kunt and Huizinga, 2010). This is consistent with my earlier finding that increasing bank size and complexity may not be a desirable channel towards achieving increased earnings transparency. The recent financial crisis highlighted the "dark side" of heavy reliance on wholesale funding which consequently triggered the liquidation of banks such as Northern Rock following sudden withdrawals due to negative public signals.

Lastly, a robust funding structure is fundamentally recognised under the Basel III framework by the operationalisation of the net stable funding ratio. The financial crisis showed that bank failures are inevitable when funding is constrained, regardless of banks' compliance with regulatory solvency ratios. Essentially, banks characterised by fragile funding structures are expected to adjust their business model. However, the impact of such actions on earnings opacity is uncertain. The results show a significantly negative effect on the opacity measures both during the short- and long-term. Generally, this supports Hypothesis 1A, 1B and 1C that banks that have a higher degree of funding stability have lower incentives to manipulate earnings. By limiting over dependence on short-term and volatile funding sources, the NSFR runs counter to the core bank objective (i.e., borrowing short and lending long) and thus, enhances a bank's net worth and earnings stability; key signals of market confidence particularly over the long-term. Market confidence is vital for both funding stability and earnings opacity particularly if a bank relies on wholesale funding to sustain its balance sheet (Ayadi et al., 2016). Banks that necessitate (or hitherto gained from) market confidence may have greater incentives to engage in earnings manipulations, even if they meet the regulatory capital requirements. These findings should however be interpreted with caution[22], with greater emphasis on the fact that the short- versus long-term impact of funding risk on earnings opacity supports the pros and cons of such regulation.

4.4.3.3. Income structure

Over the years, banks have increasingly shifted away from traditional lending activities towards non-traditional sources of income (e.g., fees, commissions, trading securities etc.). The increased profitability and competitive advantages arising from this transformation has made income diversification a fundamental part of banks' business model (Curi et al., 2015). However, it is not clear whether more diversified banking stimulate or mitigate earnings management than their more focused peers. The results in Table 4.5 show a negative impact in the short-run (within), with a positive impact on earnings opacity in the long-run (between). Specifically, although banks characterised by a greater degree of income diversification (DIVERSE) are less likely to manipulate earning in the short-term (Hypothesis 2B), they are unable to overcome this temptation in the long-term (Hypothesis 2A). In the short-term, the additional income generated from non-traditional activities may enhance bank earnings stability. Likewise, the diversification of loan portfolio across different asset classes may decrease bankruptcy risk while concurrently stabilising earnings during crisis periods (Stiroh, 2010). Moreover, strategic expansion into new loan sectors or new non-interest income generating activities may increase the bank's value. Lastly, the likelihood that managers will face greater scrutiny/pressure from investors and other stakeholders due to these positive diversification effects may mitigate incentives to manipulate earnings in the short-term.

In the long-run, more diversified firms become larger with highly complex organisational structures, resulting in greater costs of monitoring and coordinating corporate policies (Denis et al., 2002). With increasing organisational complexity results higher degree of

[22] Findings should be interpreted with less emphasis on regulatory effects of the NSFR implementation. Over time, the relation between the various funding sources and their associated costs may evolve as and when the overall banking industry demands more stable funding.

information asymmetry between bank managers, financial analysts, and financial suppliers (Thomas, 2002). Therefore, managers in more diversified banks may exploit this information asymmetry to engage in more earnings management. Given that a bank's income-generating activities do not exhibit a perfect correlation, then diversification in income sources will facilitate an optimal trade-off between the expected level of net interest income and variance of returns, which would ex-ante decrease their susceptibility to distress (Köhler, 2015). Thus, business model that relies on income diversification may help mitigate incentives to manage earnings in the short-term. However, the information asymmetry resulting from non-interest income may exacerbate bank earnings management practices.

4.4.3.4. Capital structure

While equity financing restricts the disciplinary role of creditors (Diamond and Rajan, 2001), empirical evidence suggests that higher capital reserves boost a bank's profitability and ability to overcome sudden withdrawals or losses during crisis periods (Demirguc-Kunt et al., 2013). However, attempting to optimise the capital structure via earnings management practices often affects financial reporting quality and causes extreme agency costs (Anandarajan et al., 2007). The results in Table 4.5 suggest that over the short-term, banks characterised by high capital ratios (CAP and CAP_eta) are less likely to engage in earnings management practices (Hypothesis 3). Therefore, banks with low capital ratios may tend to smoothen earnings in order to attain, improve or to maintain capital adequacy levels so as to evade punishments from regulators for failure to meet minimum regulatory requirements. Particularly, banks that are close to violating minimum capital requirements or face higher costs of violating capital requirements have greater incentives to engage in earnings manipulations (Lobo and Yang, 2001).

Over the long-term (between effects), the results indicate that the use of the capital ratio (i.e., the ratio of equity to total assets) is inefficient towards mitigating earnings management practices. However, I observe that Tier I capital as championed by the Basel committee proposal serves as a more effective tool towards safeguarding a bank's financial viability and mitigating bank earnings management practices over the long-term. Therefore, while higher capital ratios provide bigger cushions against which bad loans can be written off in the long-run, higher levels of Tier I capital ex-ante is more likely to mitigate bank distress/risk and earnings management. These results clearly support the fundamentals for the strengthening of the capital requirements through the Basel III framework and the incessant pressure on supervisory authorities to implement robust capital adequacy measures that effectively capture high-quality (i.e. core) forms of capital and bank risk.

Table 4.5: Business model and earnings opacity

	LN(DLLP-A)	ABSDLLP-A	DEVDLLP-A	LN(DLLP-B)	ABSDLLP-B	DEVDLLP-B
	(1)	(2)	(3)	(4)	(5)	(6)
WITHIN						
LOAN	-0.474**	-0.129**	-0.154***	-0.664***	-0.045***	-0.420***
	(0.185)	(0.063)	(0.058)	(0.201)	(0.011)	(0.118)
LLP	-0.302***	-0.724***	-0.619***	-0.315***	-0.028**	-0.464***
	(0.097)	(0.214)	(0.207)	(0.114)	(0.012)	(0.138)
SIZE	-0.139***	-0.273***	-0.263***	-0.135***	-0.005**	-0.129**
	(0.043)	(0.064)	(0.062)	(0.047)	(0.003)	(0.051)
DEPO	-0.317**	-0.338***	0.170	-0.364**	-0.026***	-0.261***
	(0.161)	(0.159)	(0.154)	(0.175)	(0.010)	(0.018)
STMKT	0.588***	0.365***	0.332***	0.615***	0.019***	0.515***
	(0.052)	(0.055)	(0.054)	(0.056)	(0.003)	(0.057)
NSF	-0.002**	-0.003**	-0.002*	-0.001***	-0.001***	-0.001
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
DIVERSE	-0.002**	0.001	0.000	-0.003***	-0.001***	-0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
CAP	-0.007	-0.025**	-0.020**	-0.001***	-0.001***	-0.009***
	(0.010)	(0.010)	(0.010)	(0.000)	(0.000)	(0.001)
CAP_eta	0.009	-0.026***	-0.029***	-0.052***	-0.054***	-0.064***
	(0.007)	(0.000)	(0.000)	(0.007)	(0.004)	(0.008)
ROA	-0.008	-0.007	-0.003	0.016	0.002	-0.063**
	(0.022)	(0.025)	(0.024)	(0.024)	(0.001)	(0.025)
CI	0.001**	-0.000	0.000	0.001**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LISTED	-0.002	0.001	-0.000	-0.007*	-0.000	-0.008*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.000)	(0.005)
BETWEEN						
LOAN	0.443**	0.174***	0.187***	0.532**	0.041***	0.403*
	(0.199)	(0.075)	(0.070)	(0.216)	(0.012)	(0.235)
LLP	0.960***	1.200***	1.292***	1.893***	0.007	1.327***
	(0.208)	(0.297)	(0.368)	(0.387)	(0.004)	(0.310)
SIZE	0.137***	0.268***	0.256***	0.119***	0.006**	0.114**
	(0.042)	(0.064)	(0.062)	(0.046)	(0.003)	(0.050)
DEPO	-0.289***	-0.269***	-0.213***	-0.265***	-0.021**	-0.262***
	(0.016)	(0.016)	(0.016)	(0.017)	(0.010)	(0.019)
STMKT	1.036***	0.489***	0.559***	1.449***	0.046***	0.638*
	(0.399)	(0.120)	(0.197)	(0.360)	(0.004)	(0.371)
NSF	-0.001***	-0.004**	-0.003*	-0.001***	-0.001***	0.001***
	(0.000)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)
DIVERSE	0.001***	-0.001	-0.001	0.002**	0.002***	0.002***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
CAP	0.015	0.025**	0.020*	0.011***	0.001***	0.004***
	(0.010)	(0.011)	(0.011)	(0.000)	(0.000)	(0.001)
CAP_eta	-0.011***	-0.024***	-0.027***	-0.099***	-0.064***	-0.035***
	(0.001)	(0.001)	(0.001)	(0.008)	(0.004)	(0.008)
ROA	-0.023	0.029	0.026	-0.066**	-0.003*	0.036
	(0.025)	(0.032)	(0.031)	(0.027)	(0.002)	(0.030)
CI	-0.001**	-0.000	-0.000	-0.002***	0.000	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
LISTED	-0.001	0.005	0.006	0.003	-0.000	0.007
	(0.005)	(0.004)	(0.004)	(0.005)	(0.000)	(0.005)
N	1169	1127	1127	1169	1234	1234
R2 (Within)	0.223	0.354	0.329	0.191	0.184	0.228
R2 (Between)	0.753	0.625	0.555	0.828	0.615	0.215
R2 (Overall)	0.321	0.337	0.325	0.340	0.344	0.217
Between effect	49.265***	39.672***	37.601***	53.658***	58.318***	30.706***

The table reports the estimation results from the Mundlak (1978) estimator and explains the opacity indicators using the bank-specific characteristics to capture their business model. The upper (lower) panel reports the estimated within (between) parameters, which explain to short- (vs long-) term business model effects. Further, I test for the joint significance of the between effects. All estimations use firm-year fixed effects to control for the banking environment. Standard errors robust to heteroscedasticity and clustering at bank level are given in parentheses. *, **, and *** indicates significance at 10%, 5%, 1% respectively.

4.4.4. Impact of the common factors

To augment the analysis of the business model effect on earnings opacity, I also use the factor analysis approach (see Section 4.1.2) to identify bank business models. This section therefore discusses the results based on the model that employs the common factors to explain earnings opacity. Table 4.6 reports these results by adopting a structure similar to that used for the analysis of the individual bank model characteristics. For purposes of mitigating misspecification biases, I control for all the distinct business model types. Therefore, besides the first three factors which capture the core bank business model strategies, I also incorporate the remaining six factors as well as other characteristics that may not be captured by the common factors. However, because these variables lack clear interpretations, I focus only on the impact of the three core bank strategies on earnings opacity. Since I incorporate similar information as that captured by the individual variables, I observe no significant change in the properties and goodness-of-fit of the estimated models. Accordingly, I follow the systematic approach in Section 4.2 to discuss the estimated results.

The first factor identifies a retail-oriented strategy (RETAIL) because it is positively related to funding stability, the loan, deposit and capital ratio. However, it negatively relates to size and income diversification. (see Table 4.4 and Figure 4.4). Higher values of RETAIL imply that a given bank has fundamentally comparable features of a traditional retail bank. Theoretically, greater reliance on retail deposits may either stimulate or mitigate bank earnings opacity depending on whether depositors have the incentive and/or resources to ensure effective monitoring and discipline of bank/management conduct. The results in Table 4.6 suggest that retail-oriented business models are, on average, more transparent and engage in less earnings management in the short-run. Consistent with Hypothesis 1B, this implies that in the short-term, banks that depend significantly on retail deposits have less challenges in rolling over the funds required to meet their earnings and cash flow targets and thus, a lower propensity to engage in earnings management. Moreover, retail depositors may develop incentives to either monitor bank behaviour/operations personally or pressure authorities to do so. These funding stability advantages may be eroded over the long-term particularly post implementation of explicit government deposit schemes and thus, induce bank managers to use their discretion to manipulate earnings towards meeting their private, profit, funding and capital objectives (Hypothesis 1A).

The second factor identifies a diversified business model (DIVERSIFICATION) because it captures the negative relation between a loan-dominated asset structure and highly diversified income sources. Higher values of DIVERSIFICATION imply that the business model is characterised by a highly diversified asset and income structure. Theoretically, this degree of diversification should facilitate an improvement in risk-return trade-off and thus, increase bank earnings stability. Nevertheless, the overall impact on earnings stability is also dependent on the magnitude or timing of loan loss recognition and the level of loss provisions in response to the enhanced trade-off. For instance, by overestimating the gains from income diversification, managers may engage in excessive expansion of operations which may increase the complexity of bank balance sheets, increase information asymmetry and agency problems, and, thus, lower stability while creating a fertile ground for earnings management practices. The results in Table 4.6 show a negative impact in the short-run (within), with a positive impact on earnings opacity in the long-run (between). Therefore, confirming my earlier position that while business models characterised by greater degree of functional diversification are less likely to manipulate earnings in the short-term (Hypothesis 2B), they are unable to overcome this temptation in the long-term (Hypothesis 2A). With increasing organizational complexity results higher degree of information asymmetry and agency problems between bank managers, financial analysts, and financial suppliers (Thomas, 2002). Therefore, managers in more diversified banks may exploit these biases to engage in more earnings management.

The third factor identifies a wholesale-oriented business model (WHOLESALE) because it captures the positive relation between high short-term marketable securities ratio and high non-retail or wholesale funding. Moreover, it negatively relates to deposits, income diversification and capital levels. Higher values of WHOLESALE imply that the business model is characterised by intensive borrowing from wholesale markets, where funding is generally available on rollover basis through instruments such as mortgage bonds, repurchase agreements and commercial papers. Theoretically, wholesale-oriented business models stimulate rapid expansion by mitigating the constraints imposed by local or retail deposit supply. As such, they impact the risk propensity of banks. For instance, extensive wholesale funding affects the risk-return trade-off on bank assets, increases financial fragility and income volatility and, thus, increasing the likelihood of earnings management. The results in Table 4.6 show a positive impact in the short-run (within), with an insignificant impact on earnings opacity in the long-run (between). In the short run, institutions that rely heavily on market funding have greater exposure to liquidity risk, particularly during crisis periods, as they face difficulties in rolling over short-term debt to finance illiquid assets (Hypothesis 1C). Besides, certain categories of wholesale funds (e.g., subordinated debt contracts) necessitate very strict covenants which consequently create additional incentives for managers to manipulate financial information. In the long-run, wholesale financiers may have better incentives to monitor and discipline banks due to the relative increase in their level of sophistication, although this incentive may be mitigated through collateralization. Therefore, wholesale financiers may develop better capabilities towards understanding accounting information rather than simply withdrawing funding on the basis of negative and cheap public signals. However, wholesale funding sources will always be subjected to market-wide liquidity shocks and thus, remain highly volatile, such that uninformed wholesale financiers may trigger inefficient bank liquidations (Dagher and Kazimov, 2015). Therefore, the insignificant between effect on earnings opacity is not surprising.

Table 4.6: Business model and earnings opacity – common factors

	LN(DLLP-A)	ABSDLLP-A	DEVDLLP-A	LN(DLLP-B)	ABSDLLP-B	DEVDLLP-B
	(1)	(2)	(3)	(4)	(5)	(6)
WITHIN						
RETAIL	-0.270***	-0.112***	-0.051***	-0.143***	-0.006	-0.090***
	(0.014)	(0.016)	(0.015)	(0.015)	(0.009)	(0.017)
DIVERSE	-0.184***	0.005	-0.043***	-0.272***	-0.014***	-0.071***
	(0.063)	(0.007)	(0.007)	(0.069)	(0.004)	(0.007)
WHOLESALE	0.085***	0.038***	0.038***	0.085***	0.005**	0.031***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.002)	(0.004)
ROA	-0.015	-0.001	0.002	0.010	0.001	-0.077***
	(0.021)	(0.025)	(0.024)	(0.023)	(0.001)	(0.025)
CI	0.001**	0.000	0.000	0.001**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LISTED	-0.004	-0.001	-0.002	-0.008*	-0.000	-0.009*
	(0.004)	(0.005)	(0.004)	(0.004)	(0.000)	(0.005)
BOARD SIZE	-0.648**	0.031	-0.134	-1.057***	-0.060***	-0.182
	(0.254)	(0.285)	(0.269)	(0.279)	(0.016)	(0.296)
BOARD IND	-0.186***	-0.140**	-0.152***	-0.175***	-0.007***	-0.151***
	(0.044)	(0.056)	(0.053)	(0.048)	(0.003)	(0.053)
AUDITED	0.012	-0.011	-0.010	0.012	-0.000	-0.017
	(0.011)	(0.013)	(0.012)	(0.012)	(0.001)	(0.013)
BETWEEN						
RETAIL	0.045***	0.110***	0.070***	0.114***	0.010	0.057***
	(0.017)	(0.019)	(0.018)	(0.018)	(0.010)	(0.019)
DIVERSE	0.189***	0.023***	-0.001	0.229***	0.006***	0.135***
	(0.068)	(0.007)	(0.007)	(0.007)	(0.000)	(0.008)
WHOLESALE	-0.037	-0.037	-0.040	-0.019	-0.003	-0.031
	(0.041)	(0.044)	(0.041)	(0.045)	(0.003)	(0.049)
ROA	-0.015	0.026	0.028	-0.050*	-0.002	0.057**
	(0.024)	(0.033)	(0.031)	(0.026)	(0.002)	(0.029)
CI	-0.001***	-0.000	-0.000	-0.002***	-0.000	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
LISTED	0.002	0.004	0.005	0.006	0.000	0.009*
	(0.004)	(0.005)	(0.004)	(0.005)	(0.000)	(0.005)
BOARD SIZE	0.677**	-0.139	-0.058	0.868***	0.038**	0.384
	(0.284)	(0.311)	(0.294)	(0.311)	(0.017)	(0.326)
BOARD IND	0.168***	0.130**	0.143**	0.140***	0.008***	0.131**
	(0.044)	(0.062)	(0.059)	(0.049)	(0.003)	(0.053)
AUDITED	-0.014	-0.011	-0.009	-0.018	-0.000	-0.002
	(0.013)	(0.017)	(0.016)	(0.014)	(0.001)	(0.016)
N	1129	1103	1103	1129	1136	1136
R2 (Within)	0.198	0.204	0.210	0.169	0.102	0.191
R2 (Between)	0.743	0.331	0.365	0.750	0.644	0.101
R2 (Overall)	0.308	0.197	0.217	0.316	0.291	0.165
Between effect	48.031***	20.142***	22.757***	49.891***	47.228***	22.725***

The table reports the estimation results from the Mundlak (1978) estimator and explains the opacity indicators using the common factors to capture their business model. The upper (lower) panel reports the estimated within (between) parameters, which explain to short- (vs long-) term business model effects. Further, I test for the joint significance of the between effects. All estimations use firm-year fixed effects to control for the banking environment. Standard errors robust to heteroscedasticity and clustering at bank level are given in parentheses. *, **, and *** indicates significance at 10%, 5%, 1% respectively.

4.4.5. The effect of failure risk on the business model effects

Bank failures represent key events that have significant effects not just on the banking institution, but also on other capital market participants (e.g., investors, lenders, regulators and other financial institutions) (Kupiec and Ramirez, 2013). Systematic research evidence indicates that failed banks have riskier loan portfolios and thus, poor asset quality prior to failure (e.g., Berger and DeYoung, 1997; Kohler, 2015). However, evidence on whether failure risk and survivability impact the inherent business model effect on accrual earnings management is lacking. Generally, the effect is mixed based on two non-mutually exclusive hypotheses. The bad-luck hypothesis proposes that bank failures originate primarily from uncontrollable external events which consequently precipitate increases in non-performing loans for the bank. Under this scenario of externalities, I expect that low failure risk (e.g., more stable earnings) will mitigate the inherent business model effects on earnings management practices particularly during good times. However, during crisis periods, business models complemented with low failure risk will provide bigger cushions against which bad loans can be written off. Therefore, stable business models will facilitate prompt recognition of loss provisions through increasing NPLs. The moral hazard hypothesis proposes that business models complemented with relatively high failure risk (e.g., low capital) will exacerbate moral hazard incentives through increases in the riskiness of loan portfolios, and thus resulting to higher non-performing loans in the future (Berger and DeYoung, 1997). Therefore, unstable business models are more likely to support earnings management practices than their stable counterparts.

I follow the literature (e.g., Demirgüc-Kunt and Huizinga, 2010; Kohler, 2015; Mergaerts and Vander Vennet, 2016) and measure individual bank failure risk using the Z-score. The Z-score captures a banks' distance-to-default, i.e., the number of standard deviations by which a banks' ROA can deviate from its expected value for the bank to be classified as insolvent. Higher Z-score values implies a more stable (i.e., low failure or insolvency risk) bank. The Z-score is calculated as

$$Z_{it} = \frac{CAR_{it} + \mu_{it}(ROA)}{\sigma_{it}(ROA)} \qquad (4.7)$$

$$Z_{it} = \frac{CAR_{it} + \mu_{it}(ROE)}{\sigma_{it}(ROE)} \quad (4.8)$$

where CAR_{it} is the mean equity-to-assets ratio of bank *i* in year *t*, $\mu_{it}(ROA)$ and $\mu_{it}(ROE)$ are the return on assets (and equity) respectively, of bank *i* in year *t*, and $\sigma_{it}(ROA)$ and $\sigma_{it}(ROE)$ are the standard deviation of ROA (and ROE) respectively, within a three-year rolling window. To normalise the distribution and provide a clearer interpretation, I use the natural logarithm of the Z-score (Laeva and Levine, 2009). For robustness purposes and to clearly capture the effect of failure risk, I also used a dummy for low failure risk banks: an indicator equal to 1 if Z-score is above the median bank Z-score or 0 otherwise. Values of 1 therefore implies that a bank has lesser financial difficulties and thus, has a low risk of insolvency.

In Tables 4.7 and 4.8, I augment the baseline specification regressing earnings opacity on the business model factors to include interactions between the factors and failure risk (Z-score). For robustness purposes and to clearly capture the effect of failure risk, I also use a dummy for low failure risk (>50P) -an indicator equal to 1 if Z-score is above the median or 0 otherwise. Values of 1 therefore implies that the bank is financially vibrant and has lower risk of insolvency. I adopt a structure similar to that used for the analysis of the common factors to report the results. The results suggest that failure risk plays a key role in whether the choice of business model will significantly support or mitigate earnings management practices. I find that the estimated impact of the retail-oriented business models on earnings opacity remains unaffected. The coefficients of all interaction variables are negative and statistically significant under both the short- and long-term analyses. It is worthy to note that the coefficients of the interaction variables increased in magnitude, suggesting that sound banks (low failure risk) that adopt retail banking strategies engage in less earnings management. Inherently, retail-oriented funding provides greater funding stability and transparency, and thus, when accompanied by low failure risk levels should further mitigate any incentives for earnings management particularly during good times. This confirms the position that retail-oriented banks characterised by highly volatile earnings have high probability of engaging in income smoothing and earnings management activities (Jin et al., 2018).

In terms of diversification of income sources, I find that estimated impact on earnings opacity remains unchanged: negatively (positively) significant in the short-term (long-term). Nevertheless, the coefficients of all interaction variables are negative and statistically significant under both the short- and long-term analyses. While the magnitude of the interaction effects increases in the short-term effect, the coefficient turns from positive to negative in the long-term when interacted. This confirms the key role of failure risk on whether or not a business model choice stimulates earnings management practices. In the short-run, bank stability may improve by increasing the share of non-interest income, since large proportions of non-interest income decreases reliance on interest income. Given that larger liquid positions reduce the risk of distress by itself, a complement by strengthening solvency levels should further mitigate any incentives for earnings management particularly during good times. Over the long-term, increasing organisational complexity due to larger share of non-interest income may worsen information asymmetry and agency problems. However, with greater stability, scrutiny and solvency levels, any adverse practices associated with a highly diversified asset and income structure (e.g., earnings manipulation) are mitigated.

Under wholesale-oriented business model, I find a positively (negatively) significant impact on earnings opacity in the short-term (long-term). The coefficients of the interaction variables are all negative and statistically significant particularly under the long-term analyses. In the short run, reliance on market funding decreases the rate of return on assets, and exacerbates financial fragility (i.e., distance to default), the volatility of bank income and stock returns (Demirgüc-Kunt and Huizinga, 2010). However, the price of wholesale funds also adjusts rapidly to reflect bank riskiness (Kohler, 2015). Therefore, although wholesale-oriented banks may be more risky, greater bank solvency levels will promptly be incorporated into valuations and thus, should lessen the incentives for earnings management. In the long-run, wholesale financiers become aware of borrowing firms' shortcomings and may therefore develop better incentives and/or increase in their level of sophistication towards monitoring and disciplining banks. Therefore, as wholesale financiers develop better capabilities towards understanding accounting information, more sound and solvent banks would be less likely to manipulate earnings. Collectively, the findings suggest that bank supervision and research should incorporate failure risk as well as other conventional determinants of troubled banking institutions in the analysis of business model choice/strategies. Also, supervisory authorities should closely monitor solvency ratios prudently and necessitate proactive steps towards augmenting or increasing the ratios when they decline, as envisaged under the prompt corrective action feature of the FDICIA.

Table 4.7: Business model, failure risk and earnings opacity

	LN(DLLP-A)		ABSDLLP-A		LN(DLLP-B)		ABSDLLP-B	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WITHIN								
RETAIL	-0.393**	-0.526**	-0.513**	-0.598**	-0.392**	-0.422*	-0.017***	-0.010***
	(0.179)	(0.204)	(0.225)	(0.238)	(0.194)	(0.221)	(0.001)	(0.001)
RETAIL×ZS(ROA)	-0.437***		-3.485***		-0.416***		-0.035***	
	(0.079)		(0.329)		(0.086)		(0.005)	
RETAIL×ZS-Dummy		-0.885***		-1.698***		-6.229***		-0.410***
		(0.129)		(0.164)		(1.400)		(0.083)
DIVERSE	-0.268***	0.001	0.005	-0.322***	-0.334***	-0.083***	-0.017***	-0.003***
	(0.089)	(0.001)	(0.009)	(0.018)	(0.097)	(0.014)	(0.005)	(0.000)
DIVERSE×ZS(ROA)	-0.326**		-0.298*		-0.307**		-0.027***	
	(0.149)		(0.163)		(0.162)		(0.009)	
DIVERSE× ZS-Dummy		-0.138***		-0.235***		-0.149***		-0.010***
		(0.011)		(0.013)		(0.012)		(0.000)
WHOLESALE	0.149***	0.062	0.064	0.067	0.163***	0.077*	0.009***	0.002
	(0.048)	(0.054)	(0.061)	(0.062)	(0.052)	(0.059)	(0.003)	(0.003)
WHOLESALE×ZS(ROA)	0.020		-0.010		0.017		-0.001*	
	(0.015)		(0.018)		(0.016)		(0.001)	
WHOLESALE× ZS-Dummy		-0.074***		-0.022***		-0.075***		-0.005***
		(0.005)		(0.006)		(0.005)		(0.000)
Z-SCORE (ROA)	0.011	0.013	-0.020	0.006	0.016	0.023*	0.001	0.001
	(0.013)	(0.011)	(0.017)	(0.011)	(0.014)	(0.012)	(0.001)	(0.001)
ROA	-0.020	-0.022	-0.014	-0.010	-0.012	-0.005	-0.000	0.000
	(0.029)	(0.026)	(0.026)	(0.025)	(0.032)	(0.028)	(0.002)	(0.002)
CI	0.001*	0.000	0.000	0.000	0.001**	0.001**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LISTED	-0.002	-0.005	-0.001	-0.002	-0.005	-0.008*	0.000	-0.000
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.000)	(0.000)
BOARD SIZE	-0.810**	-0.423	0.217	0.428	-1.168***	-0.874**	-0.058***	-0.051**
	(0.345)	(0.347)	(0.367)	(0.400)	(0.375)	(0.375)	(0.020)	(0.021)
BOARD IND	-0.246***	-0.270***	-0.258***	-0.261***	-0.261***	-0.279***	-0.012***	-0.010***
	(0.054)	(0.058)	(0.068)	(0.070)	(0.059)	(0.063)	(0.003)	(0.004)
AUDITED	0.011	0.025*	0.008	0.000	0.016	0.027*	0.000	0.000
	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)	(0.015)	(0.001)	(0.001)
BETWEEN								
RETAIL	0.118	0.109	0.217	0.241	0.061	-0.047	0.019	0.014
	(0.189)	(0.205)	(0.209)	(0.238)	(0.205)	(0.222)	(0.012)	(0.013)
RETAIL×ZS(ROA)	-0.048		-0.049		-0.058		0.006	
	(0.093)		(0.038)		(0.101)		(0.006)	

RETAIL× ZS-Dummy		-0.041***		-0.107***		-0.111***		-0.005***
		(0.013)		(0.017)		(0.014)		(0.000)
DIVERSE	0.263**	0.088	0.123	-0.214	0.282**	0.126	0.007	-0.004
	(0.106)	(0.119)	(0.101)	(0.159)	(0.115)	(0.128)	(0.006)	(0.008)
DIVERSE×ZS(ROA)	-0.035*		-0.033*		-0.032*		-0.003**	
	(0.019)		(0.021)		(0.021)		(0.001)	
DIVERSE× ZS-Dummy		-0.099***		-0.184***		-0.113***		-0.009***
		(0.011)		(0.013)		(0.012)		(0.000)
WHOLESALE	-0.079*	-0.012**	0.055	-0.051	-0.060*	-0.001	-0.005	-0.001
	(0.042)	(0.006)	(0.070)	(0.071)	(0.046)	(0.006)	(0.003)	(0.004)
WHOLESALE×ZS(ROA)	-0.202***		-0.351**		-0.150***		-0.013*	
	(0.015)		(0.135)		(0.016)		(0.008)	
WHOLESALE× ZS-Dummy		-0.041***		-0.082***		-0.042***		-0.005*
		(0.006)		(0.006)		(0.006)		(0.003)
Z-SCORE (ROA)	-0.006	-0.010	0.009	0.005	-0.008	-0.019*	0.000	-0.001
	(0.016)	(0.010)	(0.016)	(0.013)	(0.017)	(0.010)	(0.001)	(0.001)
ROA	-0.011	0.006	0.044	0.047	-0.025	-0.022	0.001	-0.000
	(0.041)	(0.037)	(0.037)	(0.038)	(0.044)	(0.040)	(0.002)	(0.002)
CI	-0.002**	-0.001*	-0.000	0.000	-0.002**	-0.001**	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
LISTED	0.001	0.001	0.000	0.002	0.004	0.004	-0.000	0.000
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.000)	(0.000)
BOARD SIZE	0.754*	0.572*	-0.292	-0.357	0.870*	0.821**	0.023	0.030
	(0.410)	(0.345)	(0.397)	(0.386)	(0.445)	(0.372)	(0.023)	(0.020)
BOARD IND	0.216***	0.221***	0.194***	0.199***	0.206***	0.211***	0.012***	0.011***
	(0.052)	(0.054)	(0.069)	(0.069)	(0.057)	(0.058)	(0.003)	(0.003)
AUDITED	0.017	0.013	0.017	0.023	0.016	0.015	0.000	-0.000
	(0.015)	(0.014)	(0.017)	(0.017)	(0.016)	(0.015)	(0.001)	(0.001)
N	1129	1129	1133	1133	1129	1129	1136	1136
R2 (Within)	0.265	0.263	0.319	0.343	0.254	0.265	0.199	0.212
R2 (Between)	0.741	0.774	0.619	0.559	0.771	0.800	0.749	0.641
R2 (Overall)	0.359	0.357	0.331	0.338	0.380	0.383	0.384	0.332
Between effect	55.907***	55.476***	36.648***	37.766***	61.165***	61.953***	64.321***	53.084***

The table reports the results from the Mundlak (1978) estimator and explains the opacity indicators using the interaction between the common factors (business model) and bank failure risk. The upper (lower) panel reports the estimated within (between) parameters, which explain to short- (vs long-) term business model effects. Further, I test for the joint significance of the between effects. All estimations use firm-year fixed effects to control for the banking environment. Standard errors robust to heteroscedasticity and clustering at bank level are given in parentheses. *, **, and *** indicates significance at 10%, 5%, 1% respectively.

Table 4.8: Business model, failure risk and earnings opacity (alternative)

	LN(DLLP-A)		ABSDLLP-A		LN(DLLP-B)		ABSDLLP-B	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WITHIN								
RETAIL	-0.567***	-0.395**	-0.319*	-0.264	-0.577***	-0.377*	-0.019***	-0.011***
	(0.178)	(0.200)	(0.179)	(0.222)	(0.193)	(0.216)	(0.001)	(0.001)
RETAIL×ZS(ROE)	-0.655***		-0.706***		-0.873***		-0.016***	
	(0.054)		(0.049)		(0.058)		(0.003)	
RETAIL× ZS-Dummy		-0.262***		-0.064***		-0.300***		-0.017**
		(0.015)		(0.016)		(0.016)		(0.009)
DIVERSE	-0.234***	-0.026***	-0.049***	-0.036***	-0.287***	-0.035***	-0.014***	0.002
	(0.084)	(0.010)	(0.009)	(0.011)	(0.090)	(0.011)	(0.005)	(0.006)
DIVERSE×ZS(ROE)	-1.036***		-1.592***		-1.063***		-0.100***	
	(0.485)		(0.502)		(0.523)		(0.030)	
DIVERSE× ZS-Dummy		-0.209***		-0.100***		-0.268***		-0.017***
		(0.080)		(0.008)		(0.086)		(0.005)
WHOLESALE	0.171***	0.069*	0.039	0.079**	0.186***	0.074*	0.008***	0.001
	(0.045)	(0.041)	(0.044)	(0.040)	(0.049)	(0.044)	(0.003)	(0.002)
WHOLESALE×ZS(ROE)	0.050***		0.013		0.054***		0.003***	
	(0.016)		(0.016)		(0.017)		(0.001)	
WHOLESALE× ZS-Dummy		-0.121***		0.037		-0.137***		-0.009***
		(0.045)		(0.046)		(0.048)		(0.003)
Z-SCORE (ROE)	-0.047***	-0.040***	-0.035***	-0.039***	-0.051***	-0.027***	0.003	0.000
	(0.004)	(0.003)	(0.004)	(0.003)	(0.005)	(0.003)	(0.002)	(0.002)
ROA	-0.008	-0.016	-0.008	-0.001	-0.004	-0.010	-0.001	0.000
	(0.027)	(0.026)	(0.025)	(0.025)	(0.029)	(0.028)	(0.002)	(0.002)
CI	0.000	0.000	-0.000	0.000	0.000	0.001*	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LISTED	-0.003	-0.003	-0.003	-0.001	-0.006	-0.006	-0.000	-0.000
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.000)	(0.000)
BOARD SIZE	-0.448	-0.607*	0.155	-0.135	-0.724**	-0.939***	-0.034*	-0.050***
	(0.308)	(0.318)	(0.323)	(0.365)	(0.333)	(0.343)	(0.018)	(0.019)
BOARD IND	-0.315***	-0.339***	-0.290***	-0.210***	-0.330***	-0.366***	-0.015***	-0.016***
	(0.058)	(0.060)	(0.066)	(0.067)	(0.063)	(0.065)	(0.004)	(0.004)
AUDITED	0.008	0.019	-0.009	-0.010	0.008	0.023*	-0.000	0.000
	(0.012)	(0.012)	(0.013)	(0.014)	(0.013)	(0.013)	(0.001)	(0.001)
BETWEEN								
RETAIL	0.298	0.035	0.253	0.239	0.262	-0.020	-0.026**	0.016
	(0.196)	(0.214)	(0.207)	(0.242)	(0.211)	(0.230)	(0.012)	(0.013)
RETAIL×ZS(ROE)	0.072		-0.072		0.097		-0.001	
	(0.058)		(0.055)		(0.063)		(0.004)	
RETAIL× ZS-Dummy		-0.264*		-0.100***		-0.294*		-0.017*
		(0.144)		(0.016)		(0.155)		(0.009)
DIVERSE	0.288***	0.065	0.176***	-0.042	0.315***	0.036	0.010*	-0.009
	(0.096)	(0.098)	(0.093)	(0.117)	(0.104)	(0.106)	(0.006)	(0.006)
DIVERSE×ZS(ROE)	0.083*		0.161***		0.081		0.008***	
	(0.049)		(0.053)		(0.053)		(0.003)	
DIVERSE× ZS-Dummy		-0.176**		-0.070***		-0.221***		-0.016***
		(0.079)		(0.008)		(0.085)		(0.005)
WHOLESALE	-0.114**	-0.008	0.035	-0.084*	-0.103*	0.006	-0.008**	-0.000

	(0.049)	(0.047)	(0.057)	(0.049)	(0.053)	(0.051)	(0.003)	(0.003)
WHOLESALE×ZS(ROE)	-0.398**		-0.155		-0.410**		-0.028***	
	(0.184)		(0.186)		(0.199)		(0.010)	
WHOLESALE× ZS-Dummy		-0.097**		-0.071***		-0.110**		-0.010***
		(0.049)		(0.005)		(0.052)		(0.003)
Z-SCORE (ROE)	0.088*	0.035	-0.053	0.039	0.106**	0.019	0.000	-0.001
	(0.049)	(0.028)	(0.050)	(0.042)	(0.053)	(0.031)	(0.003)	(0.002)
ROA	-0.016	-0.003	0.067	0.018	-0.027	-0.008	0.001	0.000
	(0.044)	(0.041)	(0.046)	(0.047)	(0.048)	(0.044)	(0.003)	(0.002)
CI	-0.001*	-0.002**	0.001	-0.001	-0.001*	-0.002**	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
LISTED	0.006	0.002	0.003	0.006	0.010**	0.006	0.000	-0.000
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.000)	(0.000)
BOARD SIZE	0.591*	0.627*	-0.128	-0.014	0.699*	0.737*	0.021	0.026
	(0.352)	(0.356)	(0.351)	(0.414)	(0.380)	(0.384)	(0.020)	(0.020)
BOARD IND	0.276***	0.287***	0.269***	0.187***	0.272***	0.292***	0.015***	0.016***
	(0.056)	(0.054)	(0.070)	(0.068)	(0.060)	(0.059)	(0.003)	(0.003)
AUDITED	0.009	0.014	0.014	0.010	0.009	0.013	-0.000	-0.000
	(0.014)	(0.014)	(0.017)	(0.018)	(0.015)	(0.015)	(0.001)	(0.001)
N	1129	1129	1133	1133	1129	1129	1136	1136
R2 (Within)	0.350	0.315	0.396	0.374	0.331	0.305	0.233	0.268
R2 (Between)	0.684	0.783	0.420	0.089	0.756	0.818	0.803	0.747
R2 (Overall)	0.407	0.399	0.392	0.321	0.431	0.427	0.414	0.415
Between effect	68.549***	66.527***	47.625***	34.975***	75.755***	74.459***	75.586***	75.758***

The table reports the results from the Mundlak (1978) estimator and explains the opacity indicators using the interaction between the common factors (business model) and bank failure risk. The upper (lower) panel reports the estimated within (between) parameters, which explain to short- (vs long-) term business model effects. Further, I test for the joint significance of the between effects. All estimations use firm-year fixed effects to control for the banking environment. Standard errors robust to heteroscedasticity and clustering at bank level are given in parentheses. *, **, and *** indicates significance at 10%, 5%, 1% respectively.

4.4.6. Robustness checks: Using alternative earnings opacity measures

First, the alternative opacity measures allow us to robustly assess whether or not the main findings are sensitive to the measures utilised. Constructing a measure to accurately capture earnings opacity is not straightforward, particularly because managerial traits and behaviours are unobservable (Armstrong et al., 2010). In recent years, banks have increasingly adopted the use of securities for earnings manipulation, partly due to increased innovation in credit risk modelling, increased balance sheet size, and low cost of managing the process (Altunbas et al., 2011; Cohen et al., 2014; Fan et al., 2019). Accordingly, I use the discretionary realised gains and losses of securities model (Barth et al., 2017; Dong and Zhang, 2018) to measure earnings opacity. This is specified as:

$$RGLS_{i,t} = \beta_0 + \beta_1 Size_{i,t} + \beta_2 UGLS_{i,t} + \varepsilon_{i,t} \quad (4.4)$$

where $RGLS_{i,t}$ denotes realised gains and losses of securities scaled by total assets (including realised gains and losses from available-for-sale securities and held-to-maturity securities); $Size_{i,t}$ denotes the natural logarithm of total assets; and $UGLS_{i,t}$ denotes unrealised gains and losses of securities scaled by total assets. DRGLS is captured via the residuals ($\varepsilon_{i,t}$) with higher values indicating higher earnings opacity.

In addition, the complexity of loan portfolios ensures that LLP can serve as safeguard against expected losses and thus, increasing managerial discretion for earnings manipulation (Laeven and Majnoni, 2003). By opportunistically delaying the recognitions of expected losses, banks can circumvent capital requirements and increase future profitability (Fan et al., 2019). In line with Bushman and Williams (2015), I use the delayed expected loan loss recognition model, which captures bank loan transparency to also measure of earnings opacity. I estimate the following models:

$$LLP_{i,t} = \beta_0 + \beta_1 \Delta NPL_{i,t-2} + \beta_2 \Delta NPL_{i,t-1} + \beta_3 Capital\ Ratio_{i,t-1} + \beta_4 Earnings\ before\ LLP_{i,t} + \beta_5 Size_{i,t-1} + \varepsilon_{i,t} \quad (4.5)$$

$$LLP_{i,t} = \beta_0 + \beta_1 \Delta NPL_{i,t-2} + \beta_2 \Delta NPL_{i,t-1} + \beta_3 \Delta NPL_{i,t} + \beta_4 \Delta NPL_{i,t+1} + \beta_5 Capital\ Ratio_{i,t-1} + \beta_6 Earnings\ before\ LLP_{i,t} + \beta_7 Size_{i,t-1} + \varepsilon_{i,t} \quad (4.6)$$

where $LLP_{i,t}$ denotes loan loss provisions scaled by total loans for bank i in year t, ΔNPL denotes the change in non-performing loans scaled by total loans, $Capital\ Ratio$ is the Tier 1 capital ratio, $Earnings\ before\ LLP$ denotes earnings before loan loss provisions scaled by total loans, and $Size$ denotes the natural logarithm of total assets. DELR is measured as the incremental R^2, i.e., the difference between the adjusted R^2 in Eqn. (4.5) and (4.6). Higher DELR indicates prompt recognition of expected losses. Generally, banks that recognize loss provisions promptly increase their NPLs while concurrently anticipating future non-performance. Conversely, banks that delay loss recognition of their current NPLs also fail to foresee poor future performance.

Panel A of Tables 4.9 and 4.10 reports the regression results using these alternative opacity measures as dependent variables. The results corroborate the earlier findings. Under asset structure, LOAN, LLP and SIZE support (mitigate) long-term (short-term) earnings opacity as indicated by the significantly positive (negative) impact on the opacity measures. For liability structure, retail-oriented banks (DEP) are more transparent and engage in less earnings management practices both in the short- and long-term. In contrast, wholesale-oriented business models (STMKT) expose banks to greater liquidity risk and thus increases the probability of earnings manipulation both in the short- and long-term. The short-term findings are confirmed under the common factor analysis. However, the long-run results indicate that the funding stability advantages associated with retail-oriented business models (RETAIL) may be eroded over the long-term particularly post implementation of explicit government deposit schemes and thus, induce bank managers to use their discretion to manipulate earnings towards meeting their private, profit, funding and capital objectives. Similarly, wholesale financiers may have better incentives to monitor, discipline and understand accounting information due to the relative increase in their level of sophistication, although this incentive may be mitigated through collateralization. Overall, banks characterised by high levels of funding stability (NSF) by limiting over dependence on short-term and volatile wholesale funding sources should have lower incentives to manipulate earnings both in the short- and long-term. Under income structure, banks characterised by a greater degree of income diversification (DIVERSE) are less likely to manipulate earning in the short-term, but they are unable to overcome this temptation in the long-term. These findings are confirmed by the common factor analysis for both the short- and long-term. Under capital structure, banks characterised by high capital ratios (CAP and CAP_eta) are less likely to engage in earnings management practices in the short-term. However, the long-term analysis confirms that Tier I capital under the Basel rules serves as a more effective tool towards safeguarding a bank's financial viability and mitigating bank earnings management practices.

Panel B of Tables 4.9 and 4.10 reports the regression results using the magnitude of income-increasing (negative) and income-decreasing (positive) discretionary loan loss provisions from Eqn. (4.2) as alternative proxies for earnings opacity. While most studies examine only the income-increasing manipulation, I explore, also, the income-decreasing aspect because they are often used to smoothen income by understating earnings (via overestimated loan loss provisions) during periods of high income (Beatty and Liao, 2014). Generally, income-increasing manipulations are often given greater attention because they are induced by opportunistic motives such as overstatements in earnings (via understated loan loss provisions) and Tier 1 regulatory capital ratios during crisis periods (Jin et al., 2018). The results indicate that asset structure (i.e., LOAN, LLP and SIZE) mitigates (supports) short-term income-increasing (income-decreasing) earnings management. In the long-term, business models characterised by riskier loan portfolios and large size exacerbate both income-increasing and income-decreasing earnings management practices given that these banks face strong market pressure from financiers (Richardson, 2000). In terms of funding, retail-oriented business models (DEPO and RETAIL) mitigate both income-increasing and income-decreasing earnings management activities in the short- and long-term. Retail funding mitigates the probability of meeting-or-beating earnings target, and the degree of income smoothing via loan loss provisioning. Wholesale-oriented models (STMKT and WHOLESALE) mitigate (support) short-term income-decreasing (income-increasing) earnings management practices. Over the long-term, intensive borrowing from highly volatile funding sources exacerbate both income-increasing and income-decreasing earnings management practices to signal financial strength, garner market confidence and sustain banks' balance sheet. Collectively, business models characterised by high levels of funding stability (NSFR) should mitigate both income-increasing and income-decreasing earnings management practices given that bank earnings stability improves and thus, signalling positive information to boost market confidence. Banks characterised by a greater degree of income diversification

(DIVERSE) mitigates (supports) short-term income-increasing (income-decreasing) earnings management practices. Therefore, banks with high (low) short-term pre-managed earnings by smoothing income through income-increasing (income-decreasing) earnings management practices. In the long-term, bank managers in highly diversified large banks have greater incentives to signal positive and favourable information towards enhancing their reputation/credibility and job security by increasing DLLP and then smoothening income by decreasing DLLP to boost earnings. Banks characterised by Tier I capital under the Basel rules are more efficient at mitigating both income-increasing and income-decreasing earnings management practices. Normal capital ratios (CAP) induce income-increasing earnings management practices in the long-term. By forging a direct link between loss provisioning and the level of regulatory capital, the Basel framework lessens managerial opportunities for income smoothing through the use of income-increasing (negative DLLPs) practices (Hamadi et al., 2016). Therefore, confirming that capital rules championed by the Basel committee are more effective towards safeguarding a bank's financial viability and mitigating bank earnings management practices.

Table 4.9: Business model and earnings opacity – alternative measures/tests

	PANEL A						PANEL B			
	LN(DRGSL	ABS	DEV	LN(DERL	ABS	DEV	INCREASING		DECREASING	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
WITHIN										
LOAN	-0.021***	-0.120***	-0.023***	-0.071***	-0.122***	-0.394***	-2.033***	-2.703***	1.355***	1.802***
	(0.003)	(0.025)	(0.003)	(0.017)	(0.025)	(0.036)	(0.698)	(0.687)	(0.466)	(0.458)
LLP	-1.320***	-2.142***	-1.753***	-0.445***	-0.433**	0.301***	-1.643**	-1.720**	1.095**	1.147**
	(0.550)	(0.799)	(0.690)	(0.172)	(0.161)	(0.142)	(0.763)	(0.751)	(0.509)	(0.501)
SIZE	-0.241***	-0.288***	-0.321***	-0.291***	-0.326***	-0.388***	-0.229*	-0.308**	0.152***	0.206**
	(0.065)	(0.060)	(0.070)	(0.062)	(0.058)	(0.085)	(0.164)	(0.161)	(0.059)	(0.107)
DEPO	-0.373***	-0.125***	-0.328***	-0.372***	-0.029***	-0.246***	-1.163*	-1.563***	-0.775*	-1.042***
	(0.034)	(0.021)	(0.025)	(0.123)	(0.002)	(0.114)	(0.603)	(0.594)	(0.402)	(0.396)
STMKT	1.070***	0.089***	1.219***	0.631***	0.113***	0.903***	1.237***	1.145***	-0.825***	-0.764***
	(0.333)	(0.070)	(0.486)	(0.169)	(0.165)	(0.201)	(0.182)	(0.179)	(0.121)	(0.119)
NSF	-0.004***	-0.004***	-0.004***	-0.004***	-0.005***	-0.006***	-0.007*	-0.004	-0.005*	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.003)	(0.003)
DIVERSE	-0.002	-0.002	-0.004*	-0.005***	-0.006***	-0.008***	-0.005*	-0.006**	0.004*	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
CAP	-0.036**	-0.032**	-0.045***	-0.040***	-0.026*	-0.057***	-0.037*	-0.026	0.025	0.017
	(0.016)	(0.014)	(0.017)	(0.015)	(0.014)	(0.020)	(0.024)	(0.024)	(0.024)	(0.023)
CAP_eta	0.015	-0.013***	-0.014***	0.009	-0.015***	-0.016***	-0.038***	-0.035***	-0.025	-0.023
	(0.015)	(0.001)	(0.002)	(0.014)	(0.001)	(0.002)	(0.016)	(0.015)	(0.017)	(0.017)
ROA	-0.097**	-0.095***	-0.116***	-0.108***	-0.120***	-0.227***	0.073	0.124	-0.049	-0.083
	(0.038)	(0.034)	(0.041)	(0.037)	(0.034)	(0.047)	(0.081)	(0.080)	(0.054)	(0.053)
CI	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.002***	0.001	0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
LISTED	0.015**	0.002	0.015**	0.012**	-0.003	0.021***	-0.005	-0.064	0.003	0.043
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.008)	(0.075)	(0.074)	(0.050)	(0.049)
BETWEEN										
LOAN	0.051***	0.270***	0.059***	0.128***	0.505***	0.473***	1.778**	2.504***	-1.185**	-1.669***
	(0.003)	(0.029)	(0.004)	(0.034)	(0.197)	(0.140)	(0.753)	(0.741)	(0.502)	(0.494)
LLP	0.582**	0.679***	0.424***	0.366***	0.284***	0.054*	0.370	0.848***	0.247	0.566***
	(0.277)	(0.263)	(0.198)	(0.126)	(0.124)	(0.037)	(0.362)	(0.356)	(0.241)	(0.237)
SIZE	0.329***	0.329***	0.403***	0.448***	0.424***	0.468***	0.255	0.349**	0.270***	0.233**
	(0.068)	(0.061)	(0.073)	(0.066)	(0.060)	(0.086)	(0.161)	(0.158)	(0.107)	(0.105)
DEPO	-0.422*	-0.036	-0.369	-0.524**	-0.032	-0.336	-0.806	-1.287**	-0.537	-0.858**
	(0.256)	(0.224)	(0.273)	(0.249)	(0.222)	(0.314)	(0.600)	(0.591)	(0.400)	(0.394)
STMKT	0.166	0.950***	0.134***	0.361***	1.094***	0.022***	4.219*	2.504	2.812*	1.670
	(0.131)	(0.201)	(0.038)	(0.131)	(0.281)	(0.002)	(2.488)	(2.449)	(1.659)	(1.633)
NSF	-0.008***	-0.006***	-0.009***	-0.009***	-0.007***	-0.010***	-0.000***	-0.003***	-0.000	-0.002
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(0.003)	(0.003)
DIVERSE	0.008***	0.006***	0.009***	0.013***	0.012***	0.012***	0.003***	0.002***	0.002	0.001
	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.000)	(0.000)	(0.002)	(0.002)
CAP	0.048***	0.012	0.057***	0.061***	0.012	0.067***	0.081**	0.055	-0.054**	-0.036
	(0.017)	(0.015)	(0.018)	(0.017)	(0.015)	(0.021)	(0.037)	(0.036)	(0.025)	(0.024)
CAP_eta	-0.011***	-0.032**	-0.015***	-0.012***	-0.046***	-0.012***	-0.045*	-0.039	-0.030*	-0.026
	(0.002)	(0.015)	(0.002)	(0.002)	(0.014)	(0.002)	(0.026)	(0.026)	(0.017)	(0.017)
ROA	0.178***	0.230***	0.203***	0.229***	0.291***	0.286***	-0.120	-0.174*	0.080	0.116*
	(0.049)	(0.038)	(0.052)	(0.049)	(0.041)	(0.052)	(0.095)	(0.093)	(0.063)	(0.062)
CI	0.006***	0.006***	0.007***	0.007***	0.005***	0.005**	0.001	0.001	-0.001	-0.001
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
LISTED	-0.001	0.010	-0.000	0.001	0.019***	-0.008	-0.009	-0.011	0.006	0.007
	(0.008)	(0.006)	(0.008)	(0.008)	(0.007)	(0.009)	(0.018)	(0.017)	(0.012)	(0.012)
N	1119	1119	1119	1119	1119	1119	1234	1234	1234	1234
R2 (Within)	0.566	0.622	0.535	0.491	0.533	0.281	0.141	0.185	0.141	0.185
R2 (Between)	0.901	0.910	0.906	0.954	0.960	0.972	0.678	0.622	0.678	0.622
R2 (Overall)	0.771	0.781	0.771	0.810	0.833	0.809	0.326	0.349	0.326	0.349
Between effect	318.729***	336.130***	302.758**	501.435***	544.545**	397.357**	53.104***	58.936***	53.104**	58.936***

The table reports the results from the Mundlak (1978) estimator and explains the alternative opacity indicators using the bank-specific characteristics to capture their business model. The upper (lower) panel reports the estimated within (between) parameters, which explain to short- (vs long-) term business model effects. Further, I test for the joint significance of the between effects. All estimations use firm-year fixed effects to control for the banking environment. Standard errors robust to heteroscedasticity and clustering at bank level are given in parentheses. *, **, and *** indicates significance at 10%, 5%, 1% respectively.

Table 4.10: Business model and earnings opacity – common factors

	PANEL A						PANEL B			
	LN(DRGSL)	ABS	DEV	LN(DERL)	ABS	DEV	INCREASING		DECREASING	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
WITHIN										
RETAIL	-0.590**	-0.042**	-0.701**	-0.152***	-0.171***	-0.375***	-0.879	-0.360	-0.586	-0.240
	(0.282)	(0.025)	(0.311)	(0.029)	(0.029)	(0.038)	(0.541)	(0.531)	(0.361)	(0.354)
DIVERSE	-0.836***	-0.558***	-0.824***	-1.020***	-0.638***	-0.933***	-0.548**	-0.825***	0.365**	0.550***
	(0.184)	(0.122)	(0.190)	(0.182)	(0.122)	(0.188)	(0.235)	(0.231)	(0.157)	(0.154)
WHOLESALE	0.019	0.100*	0.015	0.086**	0.173**	0.032**	0.284**	0.277**	-0.189**	-0.185**
	(0.012)	(0.078)	(0.012)	(0.026)	(0.080)	(0.012)	(0.125)	(0.122)	(0.083)	(0.082)
ROA	-0.010	-0.059*	-0.040	-0.044	-0.133***	-0.118***	0.001	0.080	-0.001	-0.053
	(0.032)	(0.031)	(0.036)	(0.033)	(0.035)	(0.045)	(0.081)	(0.079)	(0.054)	(0.053)
CI	-0.001*	-0.001***	-0.001**	-0.001**	-0.001***	-0.001*	0.001	0.001	-0.000	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
LISTED	0.011**	0.002	0.011**	0.006	-0.005	0.013*	-0.004	-0.008	0.003	0.005
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)	(0.015)	(0.015)	(0.010)	(0.010)
BOARD SIZE	0.366	0.733*	0.487	0.660	1.142**	0.980	-2.218**	-3.589***	1.479**	2.393***
	(0.484)	(0.440)	(0.533)	(0.492)	(0.486)	(0.651)	(0.956)	(0.937)	(0.637)	(0.624)
BOARD IND	-0.253***	-0.171***	-0.347***	-0.239***	-0.206***	-0.306***	-0.380**	-0.441***	0.254**	0.294***
	(0.070)	(0.066)	(0.077)	(0.071)	(0.077)	(0.097)	(0.170)	(0.167)	(0.113)	(0.111)
AUDITED	-0.004	-0.024	-0.004	-0.031*	-0.044**	-0.039	0.038	0.008	-0.026	-0.005
	(0.018)	(0.017)	(0.020)	(0.018)	(0.019)	(0.025)	(0.043)	(0.042)	(0.029)	(0.028)
BETWEEN										
RETAIL	1.427***	0.407***	1.403***	1.276***	0.304***	1.406***	-0.255	-0.614	-0.170	-0.410
	(0.428)	(0.030)	(0.444)	(0.424)	(0.032)	(0.458)	(0.640)	(0.628)	(0.427)	(0.418)
DIVERSE	0.324***	0.409***	0.343***	0.292**	0.408***	0.358**	0.421*	0.384	0.281*	0.256
	(0.116)	(0.106)	(0.128)	(0.118)	(0.118)	(0.157)	(0.249)	(0.244)	(0.166)	(0.163)
WHOLESALE	-0.003	-0.111**	0.009	-0.078	-0.168***	-0.060	0.018	-0.191	-0.012	0.128
	(0.055)	(0.051)	(0.060)	(0.056)	(0.059)	(0.075)	(0.160)	(0.156)	(0.106)	(0.104)
ROA	0.174***	0.212***	0.208***	0.276***	0.343***	0.303***	-0.060	-0.131	0.040	0.087
	(0.061)	(0.041)	(0.063)	(0.060)	(0.042)	(0.063)	(0.092)	(0.090)	(0.062)	(0.060)
CI	0.007***	0.006***	0.007***	0.008***	0.007***	0.007***	-0.000	-0.001	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
LISTED	-0.005	0.005	-0.003	-0.000	0.017**	-0.009	-0.000	0.002	0.000	-0.002
	(0.009)	(0.007)	(0.010)	(0.009)	(0.007)	(0.010)	(0.017)	(0.017)	(0.012)	(0.011)
BOARD SIZE	-2.220***	-1.228**	-2.298***	-2.964***	-1.771***	-2.858***	1.887*	2.308**	-1.258*	-1.539**
	(0.812)	(0.554)	(0.841)	(0.804)	(0.556)	(0.850)	(1.054)	(1.032)	(0.703)	(0.688)
BOARD IND	0.354***	0.223***	0.425***	0.432***	0.302***	0.466***	0.295*	0.498***	-0.197*	-0.332***
	(0.086)	(0.068)	(0.091)	(0.086)	(0.077)	(0.102)	(0.171)	(0.168)	(0.114)	(0.112)
AUDITED	-0.027	-0.010	-0.018	-0.003	0.011	-0.001	0.082	0.006	-0.055	-0.004
	(0.035)	(0.024)	(0.036)	(0.035)	(0.025)	(0.037)	(0.052)	(0.051)	(0.034)	(0.034)
N	1119	1119	1119	1119	1119	1119	802	802	432	432
R2 (Within)	0.603	0.631	0.581	0.516	0.521	0.345	0.182	0.102	0.182	0.102
R2 (Between)	0.824	0.858	0.827	0.900	0.928	0.919	0.592	0.644	0.592	0.644
R2 (Overall)	0.694	0.721	0.692	0.705	0.783	0.717	0.264	0.291	0.264	0.291
Between effect	224.473***	273.433***	215.953***	322.156***	422.252***	260.735***	40.763***	47.228***	40.763***	47.228***

The table reports the results from the Mundlak (1978) estimator and explains the alternative opacity indicators using the common factors to capture their business model. The upper (lower) panel reports the estimated within (between) parameters, which explain to short- (vs long-) term business model effects. Further, I test for the joint significance of the between effects. All estimations use firm-year fixed effects to control for the banking environment. Standard errors robust to heteroscedasticity and clustering at bank level are given in parentheses. *, **, and *** indicates significance at 10%, 5%, 1% respectively.

4.4.6.2. Accounting standards

Given that majority of the banks in the sample use either IFRS or local GAAP to report financial results (see Figure 4.1), this section focuses on extending understanding by examining whether the choice of accounting standards can also explain the business model effect on earnings management. Theoretically, the IFRS are more principle-based and market oriented, and mandate extensive disclosure requirements relative to the local GAAP. By restricting discretionary managerial opportunities and eradicating several elements of subjectivity, the IFRS are argued to improve reporting quality and reliability (Barth et al., 2008; Leventis et al., 2011). Therefore, adopting the IFRS should boost the stability of business models and thus, mitigate incentives for earnings management behaviours. However, it is possible that by limiting managers' opportunistic use of flexibility as afforded under GAAP, the quality of reported earnings may decline. As such, IFRS adoption may not be a significant factor towards improving earnings quality and mitigating incentives for earnings management practices (see e.g., Capkun et al., 2016).

To capture the extent of these effects, I segregate the sample based on a banks' choice of accounting standard: IFRS vs GAAP. The results are reported in Panel A of Table 4.11 using a structure similar to that used in the analysis of the common factors. First, the results suggest that the estimated factors are robust to changes in the sample. Further analysis shows that for banks that are retail-oriented, both the IFRS and GAAP decrease earnings management in the short-term. However, the magnitude of effect is greater for retail-oriented banks that also adopt IFRS. Over the long-term, IFRS adoption serves as a more effective tool towards safeguarding a retail bank's reporting quality and mitigating bank earnings management practices. For banks with highly diversified income sources, I find that both the IFRS and GAAP decrease earnings management in the short-term. However, in the long-term, neither of these standard choices can mitigate earnings manipulations of highly diversified banks. The magnitude of the coefficient under both samples also looks similar. Therefore, confirming the position that earnings management behaviour may not be significantly different between banks that adopted IFRS and their local GAAP counterparts (Van Tendeloo and Vanstraelen, 2005). Under wholesale-oriented banking, the results indicate that both the IFRS and GAAP are unable to mitigate short-term earnings management practices. Although attempts can be made in the long-term through highly sophisticated rules such that market confidence increases following the adoption of IFRS, wholesale funding sources will always be subjected to market-wide liquidity shocks and thus, remain highly volatile. Therefore, the insignificant negative between effect on earnings opacity is not surprising.

4.4.6.3. Audit Quality

The role auditors play in safeguarding financial reporting quality and reliability through the audit report is fundamental, particularly during crisis periods. However, whether the effectiveness of the auditor's role in safeguarding reporting credibility can mitigate inherent riskiness of business models towards eradicating incentives for earnings management is yet to be known. Theoretically, auditors tend to respond to worsening firm conditions, inability to evaluate the accurateness of reported accruals, or the likelihood that accruals may create going-concern uncertainty by issuing more conservative reports (i.e., qualified opinions) (Tsipouridou and Spathis, 2014). Therefore, more stable business models will more likely receive unqualified audit opinions for asset realisation and going-concern. By the moral hazard hypothesis, banks operating models with relatively high failure risk and for which they receive qualified audit opinions will respond to moral hazard incentives by increasing the riskiness of their loan portfolios, which results in higher nonperforming loans on average in the future (Berger and DeYoung, 1997). In contrast, given that unqualified audit opinions signal market confidence and future earnings prospects, banks that receive unqualified opinions would have lower incentives to engage in earnings management. Specifically, banks with unqualified opinions are less likely to face significant moral hazard incentives.

To capture the extent of these effects, I segregate the sample based on whether a bank received a qualified or unqualified audit opinion. The results are reported in Panel B of Table 4.11 using a structure similar to that used in the analysis of the common factors. The results suggest that for banks that are retail-oriented or have highly diversified income sources, receiving an unqualified opinion would contribute to decreasing earnings management practices both in the short- and long-term. Therefore, suggesting that retail-oriented and highly diversified business models become more augmented towards mitigating earnings management when accompanied with unqualified audit opinion. For wholesale-oriented banks, the results indicate that neither qualified nor unqualified audit opinion can mitigate short-term earnings management practices. However, the long-term analysis suggests that unqualified audit opinion conveys more positive information to the public towards enhancing market confidence and mitigating incentives for earnings management over the long-term. Collectively, the findings suggest that auditors play key roles in safeguarding banks and mitigating incentives for earnings management practices.

4.4.6.4. Conglomerate-subsidiary effects

In recent decades, rapid consolidation of banks worldwide has resulted in the creation of multimarket or multi-industry corporations (i.e., conglomerates). Though I acknowledge that subsidiary banks may act independently, their respective parent or banking groups may also create problems that affect their earnings opacity. For instance, their distinct structure and incentive towards realising higher equity valuations may induce conglomerates to manipulate their segment earnings (e.g., by transferring profitable or toxic assets to-from their subsidiaries, related party transactions, etc.) (You, 2014). Moreover, a lack of separate income statements for its diversified economic activities could lead to missing or omission of financial data and thus, orthodox reporting procedures of conglomerates may be unsuitable for disclosing relevant information about subsidiaries. However, the pricing power hypothesis may provide a cushioning mechanism that empowers firms to pass on any cost shocks to the customers, lessen cash flow fluctuations, and thus mitigating any incentives for earnings manipulations (Datta et al., 2013). Moreover, given that the market penalises firms for failure to meet earnings targets, banks with weak pricing power are more likely to manipulate earnings towards meeting market expectation. Nevertheless, in order to sustain such market power and outsmart competitors, conglomerates may strategically restrict and obfuscate the information available to rivals so as to gain competitive advantage. Given these mixed conclusions, I therefore examine whether financial conglomeration can mitigate or worsen the inherent riskiness of business models towards eradicating incentives for earnings management.

To capture the extent of these effects, I split the sample based on whether a bank is affiliated with a conglomerate or not. The results are reported in Panel C of Table 4.11 using a structure similar to that used in the analysis of the common factors. The results suggest that banks that are retail-oriented and have no conglomerate affiliations are less likely to manipulate earnings both in the short- and long-term. In the short-term, the impact is greater for non-affiliated retail banks. Although affiliated retail banks are able to mitigate some of the short-term incentives, the long-term evidence suggests that they have greater latitude to engage in earnings manipulation. For banks with highly diversified income sources, the results suggest that affiliated banks enjoy greater benefits from diversification particularly within the short-term and therefore, have less likelihood of earnings management. In the long-term, both affiliated and non-affiliated retail banks are unable to mitigate earnings opacity through diversification. However, the greater coefficient magnitude for non-affiliated but diversified banks indicates that they are more likely to engage in earnings manipulations possibly to capture some market power and match competition. For wholesale-oriented banks, the results indicate that neither affiliated nor non-affiliated wholesale banks can mitigate short-term earnings management practices. However, the long-term analysis suggests that although the implementation of highly sophisticated rules and regulatory requirements may boost market confidence and mitigate earnings management practices to some extent, wholesale funding sources will always be subjected to market-wide liquidity shocks and thus, remain highly volatile. Therefore, the insignificant negative between effect on earnings opacity for both affiliated nor non-affiliated wholesale banks is not surprising.

Table 4.11: Business model and earnings opacity – Further robustness tests

	PANEL A				PANEL B				PANEL C			
	IFRS		GAAP		QUALIFIED		UNQUALIFIED		CONGLOMERATE		NONCONGLOMERATE	
	ABSDLLP-A	ABSDLLP-B	ABSDLLP-A	ABSDLLP-B	ABSDLLP-A	ABSDLLP-B	ABSDLLP-A	ABSDLLP-B	ABSDLLP-A	ABSDLLP-B	ABSDLLP-A	ABSDLLP-B
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
WITHIN												
RETAIL	-0.360**	-0.251*	-0.270**	-0.143	-0.361	-0.037	-0.295**	-0.166***	-0.272***	-0.143***	-0.486***	-0.488***
	(0.174)	(0.165)	(0.137)	(0.131)	(0.229)	(0.249)	(0.137)	(0.046)	(0.014)	(0.015)	(0.026)	(0.028)
DIVERSE	-0.183***	-0.292***	-0.184***	-0.272***	0.121	0.028	-0.137**	-0.223***	-0.184***	-0.272***	-0.122*	-0.175*
	(0.067)	(0.076)	(0.063)	(0.069)	(0.237)	(0.257)	(0.068)	(0.072)	(0.063)	(0.069)	(0.088)	(0.093)
WHOLESALE	0.098**	0.110**	0.085***	0.085**	0.006***	0.031***	0.074**	0.073**	0.088***	0.085**	0.131**	0.141**
	(0.041)	(0.046)	(0.033)	(0.036)	(0.000)	(0.007)	(0.033)	(0.036)	(0.033)	(0.036)	(0.058)	(0.062)
ROA	-0.008	0.015	-0.015	0.010	-0.006	0.003	-0.016	0.006	-0.015	0.011	-0.044	-0.030
	(0.022)	(0.024)	(0.021)	(0.023)	(0.032)	(0.035)	(0.022)	(0.023)	(0.021)	(0.023)	(0.037)	(0.040)
CI	0.001**	0.001***	0.001**	0.001**	-0.000	0.001	0.000	0.001**	0.002**	0.001**	0.000	0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LISTED	-0.004	-0.009**	-0.004	-0.008*	-0.012	-0.016*	-0.009**	-0.014***	-0.004	-0.008*	0.000	-0.002
	(0.004)	(0.005)	(0.004)	(0.004)	(0.009)	(0.010)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
BOARD SIZE	-0.598**	-1.116***	-0.648**	-1.057***	-0.070	-0.317	-0.409	-0.817***	-0.648**	-1.057***	-0.381	-0.658*
	(0.280)	(0.314)	(0.254)	(0.279)	(0.785)	(0.852)	(0.266)	(0.284)	(0.254)	(0.279)	(0.362)	(0.384)
BOARD IND	-0.205***	-0.199***	-0.186***	-0.175***	-0.234**	-0.198*	-0.186***	-0.171***	-0.186***	-0.175***	-0.234***	-0.241***
	(0.047)	(0.053)	(0.044)	(0.048)	(0.106)	(0.115)	(0.046)	(0.049)	(0.044)	(0.048)	(0.072)	(0.076)
AUDITED	0.015	0.018	0.012	0.012	0.013	0.001	0.011	0.013	0.012	0.014	0.010	0.015
	(0.013)	(0.015)	(0.011)	(0.012)	(0.016)	(0.018)	(0.011)	(0.012)	(0.011)	(0.012)	(0.019)	(0.020)
BETWEEN												
RETAIL	-0.134***	-0.012***	0.045***	0.114***	0.187***	0.132***	-0.121***	-0.041***	0.044***	0.115***	-0.120***	-0.404***
	(0.019)	(0.021)	(0.017)	(0.018)	(0.047)	(0.051)	(0.016)	(0.017)	(0.017)	(0.018)	(0.035)	(0.037)
DIVERSE	0.199***	0.256***	0.189***	0.229***	-0.165	-0.090	-0.140*	-0.178**	0.189***	0.229***	0.320**	0.439***
	(0.073)	(0.082)	(0.068)	(0.074)	(0.293)	(0.319)	(0.072)	(0.077)	(0.068)	(0.074)	(0.129)	(0.137)
WHOLESALE	-0.059	-0.046	-0.037	-0.019	0.040***	0.073***	-0.044***	-0.026***	-0.038	-0.020	-0.018	-0.028
	(0.050)	(0.056)	(0.041)	(0.045)	(0.017)	(0.018)	(0.004)	(0.004)	(0.041)	(0.045)	(0.087)	(0.092)
ROA	-0.007	-0.052*	-0.015	-0.050*	-0.010	-0.038	-0.010	-0.043*	-0.018	-0.050*	-0.107	-0.218**
	(0.026)	(0.029)	(0.024)	(0.026)	(0.030)	(0.033)	(0.024)	(0.025)	(0.024)	(0.026)	(0.095)	(0.101)
CI	-0.002***	-0.002***	-0.001***	-0.002***	-0.001	-0.003	-0.001**	-0.001***	-0.001***	-0.002***	-0.002**	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
LISTED	0.002	0.007	0.002	0.006	0.019	0.021	0.008	0.013**	0.002	0.006	-0.002	0.002
	(0.004)	(0.005)	(0.004)	(0.005)	(0.013)	(0.014)	(0.005)	(0.006)	(0.004)	(0.005)	(0.006)	(0.007)
BOARD SIZE	0.619**	0.922***	0.677**	0.868***	-0.044	0.116	0.490*	0.685**	0.677**	0.868***	1.085**	1.508***
	(0.307)	(0.344)	(0.284)	(0.311)	(1.174)	(1.275)	(0.294)	(0.315)	(0.284)	(0.311)	(0.492)	(0.523)
BOARD IND	0.177***	0.159***	0.168***	0.140***	0.225*	0.182	0.183***	0.154***	0.168***	0.140***	0.196***	0.169**
	(0.046)	(0.052)	(0.044)	(0.049)	(0.130)	(0.141)	(0.044)	(0.047)	(0.044)	(0.049)	(0.068)	(0.072)
AUDITED	0.008	0.011	0.014	0.018	0.006	0.021	0.010	0.013	0.019	0.023	0.049*	0.069**
	(0.014)	(0.016)	(0.013)	(0.014)	(0.040)	(0.043)	(0.013)	(0.014)	(0.013)	(0.014)	(0.028)	(0.030)
N	592	592	642	642	457	457	777	777	740	740	494	494
R2 (Within)	0.245	0.196	0.198	0.169	0.237	0.227	0.221	0.204	0.198	0.169	0.222	0.196
R2 (Between)	0.723	0.741	0.743	0.750	0.980	0.969	0.813	0.823	0.743	0.750	0.710	0.781
R2 (Overall)	0.336	0.333	0.308	0.316	0.434	0.461	0.424	0.437	0.308	0.316	0.310	0.330
Between effect	49.010***	48.401***	48.031***	49.891***	30.701***	34.259***	61.216***	64.434***	48.031***	49.891***	29.717***	32.505***

The table reports the estimation results from the robustness tests. The upper (lower) panel reports the estimated within (between) parameters, which explain to short- (vs long-) term business model effects. All estimations use firm-year fixed effects to control for the banking environment. Standard errors clustered at bank level are in parentheses. *, **, and *** indicates significance at 10%, 5%, 1% respectively.

4.5. Conclusions

Despite the unprecedented and ongoing improvements to bank regulation over the last few decades, the inherent opacity of bank balance sheet structure continues to hinder regulation and market discipline of banks. Indeed, the core factors that propagated and amplified the recent financial crisis include increased complexity in bank business models which facilitated a lack of disclosure, transparency and fair competition amongst the major global banks such as Northern Rock. However, surprisingly, the empirical evidence lacks any formal tests to specifically justify the different business model choice of banks on earnings opacity and their motivations to report high quality accounting information. This chapter provides empirical evidence on the impact of bank business model strategies on the degree of bank earnings opacity. I employ two alternative approaches to capture the permanence and the scope of business model strategies in the UK. In the first approach, I use the individual bank characteristics to directly explain earnings opacity. The second approach employs the factor analysis to determine three key factors that capture the inherent latent strategies of business models: the retail orientation, the degree of functional diversification, and the wholesale orientation of banks. To explore the business model effects on earnings opacity, I explicitly distinguish between the short-term (within) and long-term (between) effects – temporal stableness versus stableness across banks over time. This approach is essential to the analysis although the findings suggest that earnings management across banks are generally greater relative to observed changes within banks.

The results show that retail-oriented business models lower the propensity to engage in earnings management in the short-term due to the increased transparent and stable of retail deposits. However, the funding stability advantages may be eroded over the long-term and thus, incentivise bank managers to manipulate earnings towards meeting their private, profit, funding and capital objectives. In contrast, wholesale funding increases the probability of earnings manipulation both in the short- and long-term. Although wholesale financiers may develop better capabilities and incentives to monitor and discipline banks, and attempts can be made through highly sophisticated rules to improve market confidence in the long-term, wholesale funding sources will always be subjected to market-wide liquidity shocks and thus, remain highly volatile. While banks business models characterised by greater degree of functional diversification are likely to lower earnings manipulation in the short-term, the long-term incentives cannot be mitigated. Lastly, although banks characterised by high capital ratios are less likely to engage in earnings management practices, I observe that Tier I capital as championed by the Basel framework serves as a more effective tool towards safeguarding bank's financial viability and mitigating bank earnings management practices over the long-term.

In examining whether low failure risk can mitigate the inherent business models effects on earnings management practices, I find that retail-oriented funding provides inherent funding stability and transparency, and thus, when complemented by low failure risk levels, should further mitigate any incentives for earnings management. In terms of diversification of income sources, I find that because larger liquid positions reduce any inherent risk of distress, a complement by strengthening solvency levels should further mitigate any incentives for earnings management. Over the long-term, increasing organisational complexity due to larger share of non-interest income may worsen information asymmetry and agency problems. However, with greater stability, scrutiny and solvency levels, any adverse earnings practices associated with a highly diversified asset and income structure are mitigated. Under wholesale-oriented banking, I find that although wholesale-oriented banks may be riskier, the price of wholesale funds also adjusts rapidly to reflect bank riskiness and therefore, greater bank solvency levels will promptly be incorporated into valuations to lessen the incentives for short-term earnings management. Also, as wholesale financiers develop better capabilities towards understanding accounting information, more sound and solvent banks would have less long-term earnings manipulation. The findings demonstrate that low failure risk (or greater solvency) represent an important channel in mitigating the inherent positive business model effect of on earnings management practices activities both in the short- and long-term.

Overall, the findings suggest that prudential regulation should not examine business model indicators in isolation, rather, attempts should focus on gauging the joint impacts of these interconnected strategic choices. Bank supervision and research should also incorporate failure risk as well as other conventional determinants of troubled banking institutions in the analysis of business model choice/strategies. Furthermore, supervisory authorities should closely monitor solvency ratios, sustainability strategies, and compulsory risk governance standards prudently, and necessitate proactive steps towards augmenting these mechanisms when they weaken or decline, as envisaged under the prompt corrective action feature of the FDICIA. The need to understand the effect of these interventions towards isolating the economic value and earnings risks that arise from the institution's behavioural adjustments is also paramount. As a minimum, supervisory authorities should form a clear view on how the stability of business models can adversely affect an institution's earnings and economic value in order to draw insights on both the short- and long-term threats to accrual manipulations. These recommendations are consistent with the principles and standards of the European Banking Authority to supervisory agencies, as detailed in the Supervisory Review and Evaluation Process (SREP) to serve as the roadmap for supervisory stress testing of European banks (EBA, 2018). The analysis may thus provide guidance on the relevance of the distinct business model choices and how their impact on bank earnings opacity may be evaluated.

Chapter 5

Conclusions

5.1. Summary and main findings

The overall aim is to bridge the gap between interbank funding decision and bank's strategic choices, and whether the choice of bank business model drives a bank's decision to manage their financial statements to smooth earnings. The growing importance of interbank money markets, which allows banks to transact among themselves using various financial instruments that cover maturities spanning one day to one year, have been blamed for the systemic exposures that emanated due to the 2007-09 global financial crisis (Georg, 2013; Lucchetta, 2015). More importantly, the recent financial crisis was characterised by aggravated liquidity hoarding due to fear of counterparty risk in the interbank market as bank business models allowed banks to delay and hide disclosure of losses on Asset Backed Securities from credit and liquidity risk (Barrell and Davis, 2008). These subsequently highlighted the "dark side" of heavy reliance on wholesale (or interbank) funding and consequently triggered the liquidation of banks such as Northern Rock following sudden withdrawals due to negative public signals.

As competitive and liquidity pressures increased, several regulatory frameworks were enacted by regulatory authorities to safeguard the banking sector (Afonso et al., 2019). However, practically, banks are performance-driven institutions (Acharya, 2009). Therefore, as competitive and liquidity pressures continue to rise to unprecedented levels, banking institutions developed new strategies to sustain their performance and ensure survival in the constantly changing financial and economic environment. Given their distinct business models, objectives and regulatory constraints, they continued to assume higher risks by circumventing the new regulations towards achieving their performance and revenue goals. This is evidenced by prior studies such as Chortareas et al., (2013) who contend that the banking sector complexity can be attributed to the rise of external and uncontrollable factors which championed key performance interventions and strategies towards enhancing bank profits and stability. In line with these goals, Curi et al. (2015) advocate that refocusing a bank's strategy to emphasize greatly on assets, funding, and income efficiency may represent an effective and efficient banking strategy, particularly for new entrants. In some cases, these banks resorted to anti-competitive conducts by grouping together (collusion) and/or merging (monopolization) to deliberately manipulate the benchmark interbank rate and/or their true earnings position (opacity), and using various financial instruments to obtain mutual benefits that lead to cost savings and increased profits (Schrimpf and Sushko, 2019). This thesis therefore seeks to employ recent methodological approaches to provide new insights that enhance understanding on a banks' incentives to use interbank funds, and their effects on bank strategic choices (conduct), performance and earnings opacity in the UK.

To address the overall objective, the thesis is segregated into three key empirical essays, presented as chapters. First, the thesis investigates the importance of bank risk exposures through interbank funding on bank efficiency levels (Chapter 2). The chapter contends that although unsecured interbank markets enable banks to lend or borrow funds towards achieving their performance objectives, they also expose banks to various risks (e.g., credit and liquidity risk) which trigger changes in bank risk management and performance. To gain more insights about these linkages and design a comprehensive performance measure, I conceptualized the overall bank performance management process as a multi-stage process with feedback and alliance where the alliance structure captures the endogenous interaction between interbank funding and bank risk. More importantly, I employ a three-stage network DEA framework with feedback and alliance to model the inter-temporal relationships among interbank funding, bank risk and efficiency. In the second objective, I go beyond objective one to examine whether a concentrated interbank market stimulate bank collusion or monopolistic pricing towards enhancing performance (Chapter 3). Therefore, rather than employing independent firm specific characteristics, I employ market-level conditions to gauge bank-level and interbank performance under the contention that to achieve their performance goals, banks will tend to adapt to market changes (structure). Where the interbank market is characterized by a concentrated structure, this may create incentives for collusion and other anti-competitive behaviours. Under such scenario, collusion or monopolistic pricing may ensure that larger banks often have better investment opportunities both within and outside the financial network. To advance knowledge and insight on the SCP within the interbank context, I use an approach that incorporates the role of bank conduct in the structure-performance nexus to offer a valid confirmation of SCP paradigm. Lastly, the third objective (Chapter 4) extends both objective one and two by examining whether the choice of business model drives a bank's decision to manage their financial statements to smooth earnings, circumvent capital requirements, and/or decrease taxes. Chapter 4 contends that the degree of bank's earnings opacity (as observed in the case of Northern Rock Bank), is dependent on the choice of bank business model: retail-oriented, wholesale-oriented, and diversified strategy. I employ two alternative approaches: (i) explaining earnings opacity directly through the individual bank characteristics, (ii) using the common factors based on the factor analysis to capture inherent latent strategies of business models. Further, to improve understanding and knowledge on the business model effects, I explicitly distinguished between short-term (within) and long-term (between) effects – temporal stableness vs stableness across banks over time.

Generally, the findings suggest that overall bank performance management is achieved via a complement of good alliance between risk and funding, and financial performance. Furthermore, high financial or overall performance may not imply better risk management or allied process performance. Rather, banks are inherently performance driven institutions whose performance objectives are independently optimal, but aggregately suboptimal. Therefore, given their distinct business models, objectives and regulatory constraints, the interbank market structure provides a channel for banks to collude and engage in monopolistic pricing in the market for bank and business loans, to consequently increase bank performance. Therefore, confirming the presence of lending relationships (Anand et al., 2015; Bräuning and Fecht, 2016) and providing support for the validity of the SCP hypothesis in an interbank context. Finally, further analyses show that the choice of bank business model – i.e., retail-oriented, wholesale-oriented, or diversified business strategy, drives a bank's decision to manage their financial statements to smoothen earnings, circumvent capital requirements, and/or decrease taxes. Although retail-oriented banks have lower propensity to engage in earnings management, the funding stability advantages may be eroded over the long-term and thus, increase incentives for earnings management over the long-term. Similarly, while greater degree of functional diversification is likely to lower earnings manipulation in the short-term, the long-term incentives cannot be mitigated. However, wholesale funding increases the probability of earnings manipulation both in the short- and long-term. Overall, a complement of low failure risk mitigates the inherent business models effects on bank earnings management practices.

5.2 Contributions and policy implications

This thesis makes some important contributions to the banking literature. Firstly, Chapter 2 extends the contributions of Liu et al. (2017) and Lucchetta (2015), who proposed that endogenous individual bank performance objectives such as efficiency levels are imperative to understanding the evolution and malfunctioning of interbank markets. In doing so, the study answers the call of Delis et al. (2015) and Tsolas and Charles (2015): to design a model takes into account the potential endogeneity arising from the bi-directional causality between risk and efficiency. Specifically, the thesis proposes a model that incorporates risk and account for the endogeneity features. Secondly, examining bank performance via a three-stage model is still in its embryonic stage. This thesis builds on the DEA and the two-stage network model with feedback (Liang et al., 2011) and alliance (Galagedera et al., 2018) to model the inter-temporal relationships among interbank funding, bank risk, and efficiency for UK banks. Thirdly, the chapter offers some new insights to policymakers to develop very close coordination and cooperation with banks in order to understand their risks and develop approaches to mitigate them in a sufficiently broad and comprehensive manner. The findings from the efficiency analysis will assist bank management decision-making on identifying operational areas that necessitate urgent improvements to support future growth strategies. The coverage of bank performance appraisal in this thesis is much broader and offers further insights towards facilitating a complete understanding of bank production systems. Last but not least, the chapter employs a composite index to examine efficiency in the usage (implied in the model) of internal resources that link multiple stages. The bank performance network representation in this thesis considers two types of linkages and derives a composite measure to determine efficient internal resource usage in the overall bank performance management process. The findings suggest that the internal resource imbalance index may enhance the discriminatory power of performance appraisal via network DEA models where internal resource imbalance is allowed.

In Chapter 3, the study fills a void, firstly, by developing a SCP model for the interbank market. The chapter contends that, by engaging in interbank operations, banks can also change their behaviour. Despite the status of the London Interbank Market as a crucial liquidity house for banks and its rate benchmarking several key rates globally (Abrantes-Metz et al., 2012; McAndrews et al., 2017) to date, there has been no published work in this area. The findings provide some insights that suggest that the interbank market structure has effect on bank conduct and subsequently performance (cost or profit efficiency) of trading banks. Secondly, the chapter adds to the literature on monopolistic/oligopolistic competition and collusion (e.g., Sannikov and Skrzypacz, 2007; Coccorese, 2009; Corbae and Gofman, 2019). The findings show how bank interactions and incentivised behaviour in one market may drive collusion in another market. This channel is distinct to evidence on industrial organisations given that non-financial institutions that are competitors cannot give "loans" to themselves, but financial institutions, such as banks, can. Key policy implications are that banks (especially larger banks) can earn abnormal profits partially through anticompetitive behaviour when the interbank market is highly concentrated to stimulate collusion and monopolistic pricing. Accordingly, consolidation activities of banks must be effectively monitored/scrutinised to prevent banks from holding/controlling substantial resources that enables them to create/possess extensive market power. Thirdly, given the conflict between the two competing SCP hypotheses, it is imperative to identify which appropriately explains interbank performance in UK banking sector. Once identified, it can offer valuable policy implications for regulators. While it may be individually advantageous for banks to collude or monopolise financial networks for abnormal gains, the resulting global network structure – the aggregated decisions of all of the economic agents at once, and which has been proven to have a core–periphery structure – may be exposed to greater systemic risks. Finally, in line with recent work and developments – i.e., monitoring/scrutiny of consolidation activities – (Adams and Mehran, 2012; Srivastav and Hagendorff, 2016; Akbar et al., 2017), the chapter extends the narrow confines of the SCP by incorporating issues related to governance and reforms, and integrating UK's unique banking structure (i.e., ownership, consolidation and board structure). It is imperative for antitrust policy to examine whether these factors affect the SCP nexus. If they do, then antitrust interventions that focus solely on the traditional SCP tests may be inefficient. For instance, if the consolidation activities are driven by banks' motive to obtain monopolistic profits, then this may hurt the economy by making the interbank and intermediation process very costly. Overall, the chapter transcends the boundaries of the normal SCP regression model to provide a more sophisticated and legitimate test for both the market-power and the efficient-structure hypotheses in an interbank setting.

Chapter 4 contributes to the banking literature by providing first hand evidence on the relationship between bank business model strategies and earnings opacity. Secondly, the chapter adds to the growing literature on business model strategies by providing a short- versus long-term perspective under which I derive key implications for earnings opacity. Thirdly, it complements existing approaches of identifying business models by employing factor analysis to robustly identify and account for the impact of key business model strategies on earnings opacity. Unlike Köhler (2015) and Mergaerts and Vander Vennet, (2016) who use two variables to identify business models, I use three variables with the third variable accounting for the reliance on short-term wholesale funding in the UK and Europe. Fourthly, in line with recent developments, the chapter extends the confines of the business model nexus to incorporate issues related to accounting rules and reforms, and integrates UK's unique banking structure (i.e., accounting standards, audit qualification and conglomerate-subsidiary effect). It is imperative for policy makers to examine whether these factors can mitigate or worsen the inherent riskiness of business models towards eradicating incentives for earnings management. If they do, then supervisory authorities should monitor banks prudently and necessitate proactive steps towards augmenting or increasing the regulatory ratios when they decline, as envisaged under the prompt corrective action feature of the FDICIA. Lastly, the chapter pulls together the literature on business models and bank failure to explain earnings opacity of banks. Although business models and bank failure have documented strong theoretical implications (see e.g., Kohler, 2015), this chapter, to the best of my knowledge, is the first to examine their joint effects on earnings opacity. By doing so, the chapter helps to address potential regulatory and supervisory concerns about whether, and to what extent, bank failure risk exacerbates misreporting of financial information and thus. hindering bank disclosure requirements. Simply, the chapter sheds light on whether there is an optimal business model and a level of failure risk at which opacity is less costly in banking. This question is crucial in the sense that all three constructs (i.e., business model, bank failure and earning opacity) limit bank monitoring and can have extreme cost implications (Bushman and Williams, 2015).

The policy implications of this thesis are also relevant in the context of the UK banking system given the significant and ongoing regulatory changes in the banking industry. Similar to other jurisdictions, the financial crisis was attributed to poor institutional practices of banks particularly involving the lack of disclosure, transparency and fair competition amongst the major global banks. For instance, Northern Rock –UK's fastest-growing mortgage bank at the time operated a business model with high reliance on non-retail or wholesale funding, became the first high-profile casualty of the crisis when it collapsed in September 2007. Moreover, although the wholesale funding model has cues such as the maturity and sourcing, a detailed breakdown of the model is not disclosed in the annual reports (Shin, 2009). Again, within the context of the UK, evidence emerged recently to suggest that the London Interbank Offered Rate (LIBOR) scandal is one of the key causes of the financial crisis (Vaughan and Finch, 2017; Fosu et al., 2018). The period envisaged a rise in regulatory lapses that stimulated greater collusion by mandated global banks to deliberately manipulate the LIBOR (Duffie and Stein, 2015). More importantly, the crisis period was characterised by aggravated liquidity hoarding due to fear of counterparty risk in the interbank market as bank business models allowed banks to delay and hide disclosure of losses on Asset Backed Securities from credit and liquidity risk (Barrell and Davis, 2008). These and many other opaque bank practices have recently been identified, usually leading to criminal prosecutions, fines and long-term imprisonments (Vaughan and Finch, 2017). Consequently, raising critical issues that necessitate supervisory attention and intervention.

5.3. Directions for future research

To conclude this thesis, this section provides an outlook on key avenues for possible future works. With respect to the discussions in Chapter 2, the proposed envelopment model may have applications beyond interbank or bank efficiency assessment. Another area of application to banks would be appraisal of outsourced key segments. It is standard practice for banks to outsource a range of their business activities either domestically and/or cross-border. Though outsourcing creates benefits (such as cost savings, accessibility to sophisticated talent pool, better or improved funding terms, among others), common risks include contagion via exposure to cross-border operations, which may serve as channel for operational and/or financial distress. The proposed network representation can virtually accommodate these features; where some processes are undertaken in-house and the others outsourced. Also, a core contribution of the first chapter is the use of the novel resource imbalance index to examine efficiency in the usage of internal resources. Future research should consider extending the application of this index to evaluate internal resource efficiency in different production models.

In the Chapters 2 and 3, future research could verify whether the individual behaviour or characteristics of bank managers affect the validity of the SCP and the business model-earnings opacity nexus. For instance, a key area to apply such models is in the study of incentive contracting under financial institutional environments. Furthermore, in Chapter 3, further research may consider going beyond testing the validity of the classical/traditional SCP model to use other models (e.g., generalized method of moments - GMM) to mitigate the potential of endogeneity issues. Finally, an interesting area that may necessitate further analysis is whether probable economic channels can explain the main findings in the third chapter. For instance, managers in banks that are owned, or supported by government may be highly sensitive to political uncertainty or instability. Similarly, the recent unprecedented trend of CEO and board connections may have implications for bank earnings opacity. Retail deposits tend to provide more funding stability relative to wholesale funding due to the existence of government deposit guarantees. Retail-oriented bank managers that are characterised by extensive political or government connections may attempt to lobby for interventions such as explicit government deposit schemes so as to weaken the incentives for monitoring and discipline. In the absence of effective depositor monitoring of banks/management, these managers may tend to supply low-quality accounting information to retail depositors. Further, retail managers who are characterised by extensive political or government connections may have high probability of engaging in income smoothing and earnings management activities towards meeting their private, profit, funding and capital objectives.

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Appendix A

I provide below the foundation of the DEA model and how it metamorphosed for purposes of the three-stage network analysis. Consider a scenario where each of a set of *n* DMUs undergo a three-stage process as depicted in Figure 2.1. Under the conventional DEA approach, banks are treated as black boxes whereby the overall environment and operations primary focus on allocating inputs to generate a set of outputs. Hence, the internal processes of the DMU and its sub-systems are overlooked. In such circumstances, any intermediate outputs between the three stages are overlooked. The bank therefore consumes A_{sx}, E_{wx}, and F_{yx} inputs and produces D_{vx} output. Starting with the constant-returns-to-scale CCR model (Charnes et al., 1981), the efficiency scores of each independent stage (1, 2 and 3) is computed as in models (A1), (A2) and (A3) respectively:

Suppose DMU_p is chosen to be assessed, the model is represented as follows:

$$e_o^1 = Max \frac{\sum_{t=1}^{j} b_t^1 B_{t0}}{\sum_{s=1}^{i} a_s A_{s0} + \sum_{o=1}^{z} g_o^1 G_{o0}}$$

Constraint $$\frac{\sum_{t=1}^{j} b_t^1 B_{tx}}{\sum_{s=1}^{i} a_s A_{sx} + \sum_{o=1}^{z} g_o^1 G_{ox}} \leq 1,$$

(A1)

$$a_s, g_o^1, b_t^1 \geq \varepsilon$$

Given that $a_s, g_o^1,$ and b_t^1 are non-negative weights and constitute the unknown weights (multipliers) and $\varepsilon \geq 0$ is the non-Archimedean infinitesimal value (Charnes and Cooper, 1984).

Model (A1) can be transformed into:

$$e_o^1 = \text{Max} \sum_{t=1}^{j} b_t^1 B_{t0}$$

Constraint $$\sum_{t=1}^{j} b_t^1 B_{tx} - \left(\sum_{s=1}^{i} a_s A_{sx} + \sum_{o=1}^{z} g_o^1 G_{ox}\right) \leq 0,$$

(A2)

$$\sum_{s=1}^{i} a_s A_{s0} + \sum_{o=1}^{z} g_o^1 G_{ox} = 1$$

$$a_s, g_o^1, b_t^1 \geq 0$$

Similarly, the model that computes e_o^2 may be specified as:

$$e_o^2 = Max \frac{\sum_{u=1}^{k} c_u^2 C_{u0}}{\sum_{t=1}^{j} b_t^2 B_{t0} + \sum_{w=1}^{m} e_w E_{w0}}$$

Constraint $\frac{\sum_{u=1}^{k} c_u^2 C_{ux}}{\sum_{t=1}^{j} b_t^2 B_{tx} + \sum_{w=1}^{m} e_w E_{wx}} \leq 1,$

(A3)

$$b_t^2, c_u^2, e_w \geq \varepsilon$$

Again, $b_t^2, c_u^2, and\ e_w$ constitute the unknown weight vectors (multipliers) and $\varepsilon \geq 0$ is the non-Archimedean infinitesimal value.

Model (A3) can be transformed into:

$$e_o^2 = \text{Max} \sum_{u=1}^{k} c_u^2 C_{u0}$$

Constraint $\sum_{u=1}^{k} c_u^2 C_{ux} - \left(\sum_{t=1}^{j} b_t^2 B_{tx} + \sum_{w=1}^{m} e_w E_{wx}\right) \leq 0,$

(A4)

$$\sum_{t=1}^{j} b_t^2 B_{t0} + \sum_{w=1}^{m} e_w E_{w0} = 1$$

$$b_t^2, c_u^2, e_w \geq 0$$

Similarly, the model that computes e_o^3 may be specified as:

$$e_o^3 = Max \frac{\sum_{v=1}^{l} d_v D_{v0} + \sum_{o=1}^{z} g_o^3 G_{o0}}{\sum_{u=1}^{k} c_u^3 C_{u0} + \sum_{y=1}^{r} f_y F_{y0}}$$

Constraint $\frac{\sum_{v=1}^{l} d_v D_{vx} + \sum_{o=1}^{z} g_o^3 G_{ox}}{\sum_{u=1}^{k} c_u^3 C_{ux} + \sum_{y=1}^{r} f_y F_{yx}} \leq 1,$

(A5)

$$d_v, g_o^3, c_u^3, f_y \geq \varepsilon$$

Again, $d_v, g_o^3, c_u^3, and\ f_y$ constitute the unknown weight vectors (multipliers) and $\varepsilon \geq 0$ is the non-Archimedean infinitesimal value.

Model (A5) can be transformed into:

$$e_o^3 = \text{Max} \left(\sum_{v=1}^{l} d_v D_{v0} + \sum_{o=1}^{z} g_o^3 G_{o0}\right)$$

Constraint $\left(\sum_{v=1}^{l} d_v D_{vx} + \sum_{o=1}^{z} g_o^3 G_{ox}\right) - \left(\sum_{u=1}^{k} c_u^3 C_{ux} + \sum_{y=1}^{r} f_y F_{yx}\right) \leq 0,$
(A6)

$$\sum_{u=1}^{k} c_u^3 C_{u0} + \sum_{y=1}^{r} f_y F_{y0} = 1$$

$$d_v, g_o^3, c_u^3, f_y \geq 0$$

Moving from the black-box model, a network model incorporates the operations of the component stages to measure efficiency. Where the internal mechanisms of the overall system are incorporated, the inputs supplied externally may be directly utilised by all sub-stages, and each stage's output may form either the final outputs of the system or the intermediate/feedback output into sub-stages. In the empirical model (Figure 2.1), I cogitate that stage 1 and stage 2 operate as an allied process. I model this connection by postulating that the intermediate measures between these stages are weighted equally notwithstanding their role, either as output of stage 1 or as input to stage 2 (Kao, 2016; Guo et al., 2017). Thus, the intermediate variables between stage 1 and stage 2 have been accorded the same weighting such that in Models (A1) and (A2) $b_t^1 = b_t^2 = b_t^{1,2}$ $, t = 1, 2, \ldots, t_{1,2}$. This assumption guarantees that the implied value of stage 1 outputs linked with the intermediate variables B_{t0} is equivalent to that of the stage 2 linked inputs, i.e. $\sum_{t=1}^{j} b_t^1 B_{t0} = \sum_{t=1}^{j} b_t^2 B_{t0}$. Thus, stage 1 and stage 2 are classified as functioning under no intermediate resource imbalance (IRI). The level of IRI between the two stages is therefore specified as

$$IRI_0^{1-2} = \frac{\sum_{t=1}^{j} b_t^1 B_{t0}}{\sum_{t=1}^{j} b_t^2 B_{t0}} \quad \text{(A7)}$$

For this study, the assumption of connection on the multipliers ($b_t^1 = b_t^2 = b_t^{1,2}$ $, t = 1, 2, \ldots, t_{1,2}$) implies that $IRI_0^{1-2} = 1$.

The expression for the overall efficiency of the two allied stages, $e_o^{1,2}$ as a weighted average of stage 1 and stage 2 efficiencies, e_o^1 *and* e_o^2 such that

$$e_o^{1,2} = W_1 e_o^1 + W_2 e_o^2$$

Such that $W_1 + W_2 = 1$, where W_1 *and* W_2 are user-specified weight vectors.

Chen et al., (2009) postulate that the relative 'size' of inputs attributed to a stage indicates the standing of the stage. They employed the proportion of implied value of a stage's inputs to the implied value of the combined inputs of the stages to denote the weighting for the overall efficiency of allied stages. Given the rationality of the assumption, I adopt it to develop my input-oriented model. Hence, $W_1 and\ W_2$ is specified as

$$W_1 = \frac{\sum_{s=1}^{i} a_s A_{s0} + \sum_{o=1}^{z} g_o^1 G_{o0}}{\left(\sum_{s=1}^{i} a_s A_{s0} + \sum_{o=1}^{z} g_o^1 G_{o0}\right) + \left(\sum_{t=1}^{j} b_t^{1,2} B_{t0} + \sum_{w=1}^{m} e_w E_{w0}\right)}$$

$$W_2 = \frac{\sum_{t=1}^{j} b_t^{1,2} B_{t0} + \sum_{w=1}^{m} e_w E_{w0}}{\left(\sum_{s=1}^{i} a_s A_{s0} + \sum_{o=1}^{z} g_o^1 G_{o0}\right) + \left(\sum_{t=1}^{j} b_t^{1,2} B_{t0} + \sum_{w=1}^{m} e_w E_{w0}\right)}$$

The overall efficiency of the two allied stages, $e_o^{1,2}$ is specified as

$$e_o^{1,2} = \frac{\left(\sum_{s=1}^{i} a_s A_{s0} + \sum_{o=1}^{z} g_o^1 G_{o0}\right) + \left(\sum_{t=1}^{j} b_t^{1,2} B_{t0} + \sum_{w=1}^{m} e_w E_{w0}\right)}{\left(\sum_{s=1}^{i} a_s A_{s0} + \sum_{o=1}^{z} g_o^1 G_{o0}\right) + \left(\sum_{t=1}^{j} b_t^{1,2} B_{t0} + \sum_{w=1}^{m} e_w E_{w0}\right) + \left(\sum_{u=1}^{k} c_u^3 C_{u0} + \sum_{y=1}^{r} f_y F_{y0}\right)} \quad \text{(A8)}$$

Likewise, I specify the overall efficiency of the three combined stages, $DMUp, e_o^{1,2,3}$ as the weighted average of the allied stages efficiency, $e_o^{1,2}$, and stage 3 efficiency, e_o^3, such that

$$e_o^{1,2,3} = W_{1,2} e_o^{1,2} + W_3 e_o^3$$

Such that $W_{1,2} e_o^{1,2} + W_3 e_o^3 = 1$, where $W_{1,2} and\ W_3$ are user-specified weight vectors.

Adopting the same assumptions employed to specify $W_1 and\ W_2$, $W_{1,2} and\ W_3$, can be defined as:

$$W_{1,2} = \frac{\sum_{s=1}^{i} a_s A_{s0} + \sum_{o=1}^{z} g_o^1 G_{o0} + \sum_{t=1}^{j} b_t^{1,2} B_{t0} + \sum_{w=1}^{m} e_w E_{w0}}{\left(\sum_{s=1}^{i} a_s A_{s0} + \sum_{o=1}^{z} g_o^1 G_{o0} + \sum_{t=1}^{j} b_t^{1,2} B_{t0} + \sum_{w=1}^{m} e_w E_{w0}\right) + \left(\sum_{u=1}^{k} c_u^3 C_{u0} + \sum_{y=1}^{r} f_y F_{y0}\right)} \quad \text{(A9)}$$

$$W_3 = \frac{\sum_{u=1}^{k} c_u^3 C_{u0} + \sum_{y=1}^{r} f_y F_{y0}}{\left(\sum_{s=1}^{i} a_s A_{s0} + \sum_{o=1}^{z} g_o^1 G_{o0} + \sum_{t=1}^{j} b_t^{1,2} B_{t0} + \sum_{w=1}^{m} e_w E_{w0}\right) + \left(\sum_{u=1}^{k} c_u^3 C_{u0} + \sum_{y=1}^{r} f_y F_{y0}\right)} \quad \text{(A10)}$$

Thus, $e_o^{1,2,3}$ can be specified as:

$$e_o^{1,2,3} = \frac{\left(\sum_{t=1}^{j} b_t^{1,2} B_{t0}\right) + \left(\sum_{u=1}^{k} c_u^2 C_{u0}\right) + \left(\sum_{v=1}^{l} d_v D_{v0} + \sum_{o=1}^{z} g_o^3 G_{o0}\right)}{\left(\sum_{s=1}^{i} a_s A_{s0} + \sum_{o=1}^{z} g_o^1 G_{o0}\right) + \left(\sum_{t=1}^{j} b_t^{1,2} B_{t0} + \sum_{w=1}^{m} e_w E_{w0}\right) + \left(\sum_{u=1}^{k} c_u^3 C_{u0} + \sum_{y=1}^{r} f_y F_{y0}\right)}$$

(A11)

Following Galagedera et al., (2018), the empirical setup of the model assumes that the allied stages and stage 3 incorporate different environmental conditions regarding risk. This makes the model analogous to a two-stage model with independent functions. Under this scenario, attributing the same weight to a resource that performs a dual role may not be appropriate. Such quandaries manifest in network representation of interbank network risks and contagion. For instance, Liang et al., (2008) utilised the cooperative game approach to examine two stages that assume the role of players. Each player or stage employed the best possible weighting for its intermediate and feedback variables. Kao and Hwang, (2008) adopted a similar assumption to model its intermediate variables. Failing to incorporate this assumption exposes the model to biases associated to the standard CCR model's equal weighting (Liang et al., 2011).

In this model, I address the endogenous and duality role of risk on efficiency that is generally overlooked in the evaluation of interbank network risks and contagion. Practically, bank operations on unsecured interbank markets require compensations for facing the borrowing bank's default risk (credit risk) and the liquidity risk associated to its own future funding requirements. From this viewpoint, risk is an output factor of funding decisions, but from another viewpoint, banks must manage these risks in order to achieve better efficiency and productivity levels. Incorporating funding risk as both input and output constitutes to enhancing the resilience of the interbank network. However, in assessing a bank's performance, there is no requirement of compliance to a model-implied conditional valuation scheme that is unfavorable to banks. Thus, a bank may choose to take on more risks as and when management decides. Following this line of reasoning, I assume that banks assume different levels of risk. Therefore, I allow a fair degree of flexibility in the choice of multipliers for the intermediate variables that relate the allied stages to stage 3. Specifically, I avoid the assumption of equal weighting of multipliers for the intermediate variables between the allied stages to stage 3. Rather, the restrictions imposed on the multipliers of the intermediate measures $Q^{1,2/3}$ are $c_u^2 \geq c_u^3$ and $g_o^3 \geq g_o^1$ for $u, o = 1,2,3, \dots, u_2;\ o_3$ (Galagedera et al., 2018)[23]. This

[23] Using a metric specified as the proportion of composite output to composite input to evaluate performance requires a relatively higher composite output to input (Galagedera et al., 2018). Under stage 3, $c_u^2 \geq c_u^3$ and $g_o^3 \geq g_o^1$ for $u, o = 1,2,3, \dots, u_2;\ o_3$ are input and feedback variables and thus, evaluating

assumption ensures that the summation of the implied value of the intermediate (and feedback) variables as output (and input) of the allied stage is greater (less) than or equal to the summation of the implied value of the same set of variables as input (output) to stage 3. Thus, $\sum_{u=1}^{k} c_u^2 C_{ux} \geq \sum_{u=1}^{k} c_u^3 C_{ux}$ and $\sum_{o=1}^{z} g_o^3 G_{ox} \geq \sum_{o=1}^{z} g_o^1 G_{ox}$ for all $x = 1,2,3,\dots,n$. There is therefore the likelihood of imbalance in the implied value of intermediate variables $Q_{u,o}^{1,2/3}$. The level of IRI between the allied stages and stage 3 is determined by

$$IRI_0^{1,2/3} = \frac{\sum_{u=1}^{k} c_u^3 C_{ux} + \sum_{o=1}^{z} g_o^1 G_{ox}}{\sum_{u=1}^{k} c_u^2 C_{ux} + \sum_{o=1}^{z} g_o^3 G_{ox}} \quad \text{(A12)}$$

Such that $0 < IRI_0^{1,2/3} \leq 1$

Appendix B

The proof of lemma and theorem for hypothesising about the overall approach with alliance between stage 1 and 2 is expressed as:

H2.1: The overall process of DMU_p is efficient only when the allied stage and the performance stage is efficient $\left(e_o^{1,2*} = e_o^{3*} = 1\right)$.

Proof of Hypothesis

Lemma: Given that the allied stage of DMU_p is efficient $\left(e_o^{1,2*} = 1\right)$, then based on the first, second and last conditions of model (2.4) we have:

$$\sum_{t=1}^{j} \theta_t^{1,2*} B_{tx} - \left(\sum_{s=1}^{i} \sigma_s^* A_{sx} + \sum_{o=1}^{z} \rho_o^{1*} G_{ox}\right) \leq 0; \quad \sigma_s^*, \rho_o^{1*}, \theta_t^{1,2*} \geq 0$$

$$\sum_{u=1}^{k} \gamma_u^{2*} C_{ux} - \left(\sum_{t=1}^{j} \theta_t^{1,2*} B_{tx} + \sum_{w=1}^{m} \vartheta_w^* E_{wx}\right) \leq 0; \quad \theta_t^{1,2*}, \gamma_u^{2*}, \vartheta_w^* \geq 0$$

and

$$\sum_{t=1}^{j} \theta_t^{1,2*} B_{t0} + \sum_{u=1}^{k} \gamma_u^{2*} C_{u0} = \sum_{s=1}^{i} \sigma_s^* A_{s0} + \sum_{o=1}^{z} \rho_o^{1*} G_{o0} + \sum_{t=1}^{j} \theta_t^{1,2*} B_{t0} + \sum_{w=1}^{m} \vartheta_w^* E_{w0}$$

---

the performance of stage 3 accurately require the input values to be lower to imply that realistically $\sum_{u=1}^{k} c_u^2 C_{ux} \geq \sum_{u=1}^{k} c_u^3 C_{ux}$ and $\sum_{o=1}^{z} g_o^3 G_{ox} \geq \sum_{o=1}^{z} g_o^1 G_{ox}$ for all $x = 1,2,3,\dots,n$ holds.

Theorem: Given that stage three DMU_p is efficient $(e_o^{3*} = 1)$ and the Lemma proof above satisfies $e_o^{1,2*} = 1$, then $e_o^{1,2/3*} = 1$ since $e_o^{1,2*}$ is computed as a convex combination of $e_o^{1,2}$ and e_o^{3}. Again, given that DMU_p is efficient overall $\left(e_o^{1,2/3*} = 1\right)$, then based on the fourth condition of model (2.4) we have:

$$\sum_{t=1}^{j} \theta_t^{1,2*} B_{t0} + \sum_{u=1}^{k} \gamma_u^{2*} C_{u0} + \sum_{v=1}^{l} \varphi_v^* D_{v0} + \sum_{o=1}^{z} \rho_o^{3*} G_{o0} = \sum_{s=1}^{i} \sigma_s^* A_{s0} + \sum_{o=1}^{z} \rho_o^{1*} G_{o0} + \sum_{t=1}^{j} \theta_t^{1,2*} B_{t0} + \sum_{w=1}^{m} \vartheta_w^* E_{w0} + \sum_{u=1}^{k} \gamma_u^{3*} C_{u0} + \sum_{y=1}^{r} \aleph_y^* F_{y0}$$

By substituting into model (2.4), the resulting estimation is

$$\sum_{v=1}^{l} \varphi_v^* D_{v0} + \sum_{o=1}^{z} \rho_o^{3*} G_{o0} - \left(\sum_{u=1}^{k} \gamma_u^{3*} C_{u0} + \sum_{y=1}^{r} \aleph_y^* F_{y0}\right) = e_o^{1,2_A*}\left(\sum_{s=1}^{i} \sigma_s^* A_{s0} + \sum_{o=1}^{z} \rho_o^{1*} G_{o0} + \sum_{t=1}^{j} \theta_t^{1,2*} B_{t0} + \sum_{w=1}^{m} \vartheta_w^* E_{w0}\right)$$

From model (2.7), I estimate

$$\sum_{v=1}^{l} \varphi_v^* D_{v0} + \sum_{o=1}^{z} \rho_o^{3*} G_{o0} - \sum_{u=1}^{k} \gamma_u^{3*} C_{u0} - \sum_{y=1}^{r} \aleph_y^* F_{y0} \leq 0$$

Thus, it follows that $e_o^{1,2_A*}\left(\sum_{s=1}^{i} \sigma_s^* A_{s0} + \sum_{o=1}^{z} \rho_o^{1*} G_{o0} + \sum_{t=1}^{j} \theta_t^{1,2*} B_{t0} + \sum_{w=1}^{m} \vartheta_w^* E_{w0}\right) \leq 0$. This condition is satisfied only when $e_o^{1,2_A*} = 1$ due to the assumption that all observed values and the multipliers are positive$(\varepsilon \geq 0)$ and $e_o^{1,2_A*} \leq 1$. Thus, ensuring that $e_o^{1,2/3*} = 1$ and $e_o^{1,2*} = 1$.

Appendix C

Table 1C: Descriptive statistics

	Mean	St. Dev.	Min.	Max.	25th P	50th P	75th P	No. of banks
Interbank Fees (A_{x2})	2.79	12.02	0.01	73.83	0.12	0.28	0.61	93
Capital (A_{x1})	0.01	0.03	0.00	0.25	0.00	0.01	0.02	93
Loans and Advances (A_{x3})	0.96	0.09	0.63	1.00	0.97	1.00	1.00	85
Interbank Lending (G_{x1})	4.60	10.60	0.01	61.94	0.11	0.71	3.81	93
Interbank Borrowing (B_{x1})	0.29	0.26	0.00	0.88	0.06	0.19	0.50	93
Long-term Wholesale Borrowing (B_{x2})	0.57	0.44	0.00	2.19	0.17	0.55	0.93	93
Short-term Wholesale Borrowing (B_{x3})	0.50	0.39	0.00	1.00	0.11	0.52	0.92	93
OBS (E_{x2})	0.03	0.02	0.01	0.11	0.02	0.03	0.04	93
Deposits (E_{x1})	46.69	37.44	0.00	99.99	8.03	48.74	82.72	93
Liquidity Risk (C_{x1})	46.16	27.89	2.20	99.87	22.90	38.75	69.07	93
Credit Risk (C_{x2})	31.42	30.75	0.00	120.84	0.00	27.72	56.71	93
Solvency Risk (C_{x3})	0.21	0.58	0.00	4.89	0.00	0.12	0.18	93
Loan Loss (F_{x1})	7.72	26.60	0.00	117.64	0.16	1.22	13.56	93
Return on Asset (ROA) (D_{x1})	0.17	2.74	-23.26	5.64	0.08	0.35	0.79	93
Return on Equity (ROE) (D_{x2})	2.79	15.15	-124.69	22.71	0.70	4.01	7.37	93
Net Interest Income (D_{x4})	53.71	35.02	-37.19	108.32	33.61	63.36	79.82	93
Capital Adequacy (D_{x3})	21.42	52.41	0.00	488.00	0.00	16.90	21.50	93

The table reports the summary statistics for all variables used to estimate the relative efficiency scores (RES) in our core DEA analysis. The sample comprises 93 banks representing 75% of all banks that have operations in the UK, and are classified as commercial banks in Orbis. All variable definitions are reported in Table 2.1.

Appendix D

1A. The multi-output translog cost frontier (Eqn. 3.4) is specified as:

$$\ln\left(\frac{C}{w_3}\right) = \beta_0 + \sum_{i=1}^{2}\beta_i \ln Q_{i,t} + \sum_{i=1}^{2}\beta_i \ln\left(\frac{w_i}{w_3}\right) + \frac{1}{2}\sum_{i=1}^{2}\sum_{j=1}^{2}\beta_{ij}\ln Q_{i,jt}\ln Q_{i,jt}$$
$$+ \frac{1}{2}\sum_{i=1}^{2}\sum_{j=1}^{2}\beta_{i,j}\ln\left(\frac{w_i}{w_3}\right)\ln\left(\frac{w_i}{w_3}\right) + \sum_{i=1}^{2}\sum_{j=1}^{2}\beta_{i,j}\ln Q_{i,jt}\ln\left(\frac{w_i}{w_3}\right)$$
$$+ \ln Equity + T + T^2 + \left(v_{i,t} + u_{i,t}\right)$$
$$i = 1, \dots., N \; and \; t = 1, \dots, T \qquad \text{(D1)}$$

1B. I utilise the parameter estimates from Eqn. (D1) to generate the bank-specific relative cost efficiency score as:

$$Cost\ Eff^f = \frac{\hat{C}^{min}}{\hat{C}^f} = \frac{exp[\hat{c}(q^f, w^f)] \times exp\left(\ln \hat{u}_c^{min}\right)}{exp[\hat{c}(q^f, w^f)] \times exp\left(\ln \hat{u}_c^f\right)} = \frac{\hat{u}_c^{min}}{\hat{u}_c^f} \qquad \text{(D2)}$$

2A. The translog profit frontier (Eqn. 3.5) is specified as:

$$\ln P = \beta_0 + \sum_{i=1}^{2}\beta_i \ln Q_{i,t} + \sum_{i=1}^{2}\beta_i \ln w_i + \frac{1}{2}\sum_{i=1}^{2}\sum_{j=1}^{2}\beta_{ij}\ln Q_{i,jt}\ln Q_{i,jt}$$
$$+ \frac{1}{2}\sum_{i=1}^{3}\sum_{j=1}^{3}\beta_{i,j}\ln w_{i,jt}\ln w_{i,jt} + \sum_{i=1}^{2}\sum_{j=1}^{3}\beta_{i,j}\ln Q_{i,jt}\ln w_{i,jt} + \ln Equity$$
$$+ T + T^2 + \left(v_{i,t} + u_{i,t}\right)$$
$$i = 1, \dots., N \; and \; t = 1, \dots, T \qquad \text{(D3)}$$

2B. I utilise the parameter estimates from Eqn. (D3) to generate the bank-specific relative profit efficiency as:

$$Profit\ Eff^f = \frac{\hat{P}^f}{\hat{P}^{max}} = \frac{exp[\hat{p}(q^f, w^f)] \times exp\left(\ln \hat{u}_p^f\right)}{exp[\hat{p}(q^f, w^f)] \times exp\left(\ln \hat{u}_p^{max}\right)}$$

$$= \frac{\hat{u}_p^f}{\hat{u}_p^{max}} \qquad (D4)$$

3A. The $MC_{i,t}$ is derived from the translog cost function as:

$$\ln C_{i,t} = \alpha + \beta_1 \ln q_{i,t} + \frac{\beta_2}{2} \ln q^2{}_{i,t} + \sum_{k=1}^{3} \gamma_{k,t} \ln w_{k,i,t} + \sum_{k=1}^{3} \varphi_k \ln q_{i,t} \ln w_{k,i,t}$$
$$+ \sum_{k=1}^{3} \sum_{j=1}^{3} \delta_{i,j} \ln w_{k,i,t} \ln w_{j,i,t} + \sum_{i=1}^{3} \left(\frac{\theta_i}{2}\right) \ln w^2{}_{t,i,j} + \sum_{k=1}^{2} \pi_k\, trend^k$$
$$+ \sum_{i=1}^{3} \ln w_{k,i,t}\, trend + v \ln q_{t,j}\, trend + \varepsilon_{i,t} \qquad (D5)$$

where $C_{i,t}$, $q_{i,t}$, $w_{i,t}$, have the same definition as in Eqn. (3.4). Eqn. (3.10) includes fixed effects to account for bank-specific factors. The marginal cost is the first derivative of the cost function with respect to the output evaluated for each sampled bank as specified in Eqn. (D6):

$$MC_{it} = \frac{Cost_{i,t}}{Q_{i,t}} \left[\beta_1 + \beta_2 \ln q_{i,t} + \sum_{k=1}^{3} \varphi_k \ln w_{i,t} + vtrend_{i,t}\right] \qquad (D6)$$