Herding and Systemic Risk in Banking Sector

Frimayudha Ardyaputra

A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy in Finance

Business School
University of Strathclyde
United Kingdom
2020

Declaration of Authenticity and Author's Rights

This thesis is the result of the author's original research. It has been composed by the author and has not been previously submitted for examination which has led to the award of a degree.

Signed: *Frimayudha Ardyaputra*

Date: 16/12/2020

Acknowledgments

I would like to express my sincere gratitude to my supervisor, Professor Krishna Paudyal. Without his guidance, support and encouragement, I will not have made it this far and earned valuable skills and experience in research. I extend my thanks to Professor Andrew Marshall for his encouragement and valuable feedbacks, especially in developing the empirical chapters of this thesis into papers. I also thank Professor Jonathan Fletcher for the motivation during the first year of my study. Furthermore, I would like to say thank you to the examination committee: Professor Jonathan Williams, Dr. Chandra Thapa and Dr. Hai Zhang. It is really an honour for me to have the opportunity to discuss the thesis during viva with the experts.

I would like to express how blessed I am to have my wife, Yurie Rusfianie, whom has always been there for me. Her relentless affection and confidence in me have gave me the strength to overcome many challenges in writing this thesis. I am also indebted to all members of my extended family, especially my parents Mr. Ardhayadi and Mrs. Endang Purbandini, for their unconditional support and prayers. In addition, the journey would not have been complete without my two children, Kinaya and Keivel, whom are the source of my happiness and motivation.

I am grateful to my employer, Bank Indonesia, for the financial support. I am also indebted to Mr. Mirza Adityaswara, Mr. Doni P. Joewono, Mrs. Filianingsih Hendarta, Dr. Agusman, Dr. Arlyana Abubakar, and Mrs. Clarita Ligaya Iskandar for the opportunity to pursue my PhD at the University of Strathclyde. I would also like to offer my gratitude to Dr. Dwityapoetra S.B. and Dr. Cicilia A. Harun for their mentorship. Furthermore, I thank all of my colleagues at the Department of Macroprudential Policy of the Central Bank of Indonesia for their continous support.

I owe a special thanks to my professors at Georgetown University, Professor J. Keith Ord and Professor Allan Eberhart, for the support and inspiration to pursue a PhD in Finance. Last but not least, I am thankful to all of the staff at the department, especially Lorna and Donna, for their kind help and my PhD colleagues especially Dr. Ling Tai Hu, Dr. Rotcharin Kunsrison, Dr. Sandeep K. Rao, and Denny Andriana for the friendship.

Abstract

Systemic banking crises can cause significant disruptions in the economy (Dell'Ariccia, Detragiache and Rajan, 2008; Reinhart and Rogoff, 2014) and result in non-trivial fiscal costs (Calomiris, 1999; Dewatripont, 2014). Consequently, a great number of studies in the banking literature have been dedicated to examining systemic risk in the banking system, in particular that of too-big-to-fail banks (Shleifer and Vishny, 2010; Laeven, Ratnovski and Tong, 2016). Nonetheless, the problem of the systemic risk posed by bank herding has received less attention.

This thesis provides a rigorous empirical examination of the theory that banks herd to increase the likelihood of a collective bailout position should default occur (Acharya and Yorulmazer, 2007; Farhi and Tirole, 2012). The empirical examination is assessed by addressing three key research questions: 1) Do banks herd and can country-level factors explain herding consistent with the theory? 2) If yes, does herding pose a systemic risk? 3) How does herding affect the competition and profit of banks? These questions are addressed in three individual empirical chapters.

The first empirical chapter (Chapter 2) investigates whether banks do herd and if country-specific factors affect herding consistent with the theory. The findings support the proposition that banks do herd and that the degree of herding varies across countries. The results also show that herding is dependent on several country-specific features such as exposure to fiscal costs, banking sector characteristics, and regulatory and supervisory quality. However, contrary to the theory, the effect of shareholder protection laws on herding is not significant, possibly because banks with dispersed ownership also receive bailout subsidies when banks collectively fail.

The second empirical chapter (Chapter 3) investigates the systemic risk implications of bank herding. The findings show that the effect on systemic risk of the interaction between herding and deposits and that between herding and loans are statistically significant. The results suggest that negative externalities from excessive funding risk and liquidity risk taking may not have been fully internalised through existing prudential regulations.

The third empirical chapter (Chapter 4) examines the effect of herding on the competition and profit of banks. Empirical evidence in this chapter indicates higher competition among banks that herd compared to the rest of the banking industry. Nonetheless, herding may still be desirable when competition in the banking industry is weak. The possibility of a higher profit from low banking industry competition allows banks to compensate for the erosion in profit caused by herding. Furthermore, in the face of herding, the adverse effect of increased competition on profit is larger for banks that are followed by others compared to those that follow the leaders.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1. Introduction

The phenomenon of too-many-to-fail is frequently observed in financial crises[1] (Kroszner and Strahan, 1996; Brown and Dinç, 2011). These include the U.S. Savings and Loan Crisis of the 1980s, the Japanese Banking Crisis of the 1990s, the Asian Financial Crises in 1997–98 and the Global Financial Crisis of 2008. The problem creates time-inconsistency in bank liquidation policies. In particular, when many banks are likely to fail, a government's decision to bailout some or all of the defaulting banks is ex-post optimal (Acharya and Yorulmazer, 2007; Farhi and Tirole, 2012).

Government interventions may limit the extent of bank failures during a crisis. However, these government policies may also have significant fiscal costs and create a moral hazard problem in the banking system (Goodhart and Huang, 2005; Dewatripont, 2014). In terms of fiscal costs, Calomiris (1999) estimates that bank bailouts in the 1997 Asian Financial Crises cost approximately 20–50% of GDP for Thailand, Indonesia, South Korea and Japan. The bailout costs due to the 2008 Global Financial Crisis in the U.S. and Euro Areas were approximately 4.5% and 3.9% of GDP, respectively (Dewatripont, 2014). Total funding for the Troubled Asset Relief Program (TARP) to limit banking sector problems in the U.S. during the global financial crisis totalled a massive USD 700 billion of taxpayer money (Veronesi and Zingales, 2010). These estimates clearly suggest that bailout costs are not trivial for any government.

[1] According to Claessens and Kose (2013), a financial crisis is often related with one or a combination of the following phenomena: a significant decline in credit volume and asset prices, severe disruption in financial intermediation and external financing supply, large-scale balance sheet problems and large-scale government support.

The frequent occurrence of financial crises and the resulting costs raise the question of whether the causes of too-many-to-fail have been fully identified and addressed. Brown and Dinç (2011) find evidence of regulatory forbearance amidst the occurrence of too-many-to-fail banks in emerging markets and argue the possibility of similar cases in developed countries. They suggest that further research is required to explain whether the problem leads to ex-ante bank herding,[2] as postulated in some theoretical studies (Acharya and Yorulmazer, 2007; Farhi and Tirole, 2012).

Following the Global Financial Crisis in 2008, a number of regulatory reforms have been introduced. The most prominent include Basel III regulations (Basel Committee on Banking Supervision, 2011). The regulations aim to increase the resilience of the banking sector by strengthening the regulatory capital framework and introducing a liquidity standard. Basel III imposes both higher capital ratios and a stricter definition of Tier 1 capital. Banks must also meet a 3% leverage ratio limit based on non-risk weighted assets. In addition, liquidity standards have been introduced to reduce banks' vulnerabilities to funding shocks and over-reliance on short-term wholesale funding. The standards require banks to hold fractional reserves of liquid assets to meet short-term liquidity needs and impose a limit on maturity mismatch.

In addition to the microprudential requirements noted above, Basel III imposes requirements to address systemic risk.[3] Concerning the time-series dimension of

---

[2] Herding in this study is defined as a behaviour in which an agent intentionally or actively mimics the behaviour of other agents (Bikhchandani and Sharma, 2000). The definition is explained in more detail in the first empirical chapter ("Bank Herding and its Determinants") of this thesis.

[3] Systemic risk is defined as a risk that causes significant financial stability impairment. (The International Monetary Fund, Bank for International Settlements and Financial Stability Board, 2009). Further explanation regarding the definition of systemic risk is provided in the second empirical chapter ("Systemic Risk Implications of Bank Herding") of this thesis.

systemic risk, the regulatory framework introduces a countercyclical capital buffer to mitigate procyclicality. As for the cross-sectional dimension, designated systemically important banks are required to hold additional capital buffer against risk-weighted assets.

Benoit *et al.* (2017), however, argue that the regulations do not explicitly discourage herding. Moreover, some of the regulations may actually increase commonality across banks. The stress test, for example, requires banks to have adequate capital to absorb the same shocks, thus discouraging banks from adopting the opposite approach. Horváth and Wagner (2017) also raise the concern that the implementation of a countercyclical capital requirement creates an incentive for banks to invest in correlated activities, i.e. the kinds of policies that lead to herding.

Hence, an empirical study that investigates whether banks do herd and examines the systemic risk implications of herding is required. An understanding of the factors that drive herding in the banking sector is important, as herding may lead to credit misallocation and inefficiency in the economy, fuel procyclicality and trigger systemic risk (Acharya and Yorulmazer, 2008; Nakagawa and Uchida, 2011).

This study aims to fill the void by providing an empirical assessment of the theory that banks herd to increase the likelihood of a collective bailout position should default occur (Acharya and Yorulmazer, 2007; Farhi and Tirole, 2012). This main research objective is assessed by addressing three key research questions: 1) Do banks herd and can country-level factors explain herding consistent with the theory? 2) If yes, does herding pose a systemic risk? 3) How does herding affect the competition and profit of banks? Attempts to answer each of these questions constitute the individual empirical chapters of this thesis. Figure 1.1 illustrates how the three key research questions are connected with the main objective.

Following Bikhchandani and Sharma (2000), herding in this study is defined as a behaviour in which an agent intentionally or actively mimics the behaviour of other agents. Active herding is not spurious and is driven by non-fundamental factors such as asymmetric information, agency problem and payoff externality. The presence of active herding may cause inefficiency in the economy, as banks forgo profitable loans to other sectors of the economy. At the same time, the behaviour may also pose a systemic risk, as bank herding increases the likelihood of a collective bailout position should default occur (Acharya and Yorulmazer, 2008; Nakagawa and Uchida, 2011).

This study uses rational herding models to explain herding in the banking sector due to the likelihood of bailout. This is consistent with the related theory which assumes agents are rational. Rational herding is defined as herding that arises due to the presence of externalities, information cost or incentive issues that distort optimal decision-making (Devenow and Welch, 1996).

To provide valuable information concerning bank vulnerabilities and regulations that are relevant to the research, this study focuses on cross-country commercial banks. Usually these banks are highly regulated because of their critical roles in the economy as lender and deposit-taking institutions as well as their exposure to maturity transformation and liquidity risk.

The sample of this study covers periods ranging from 2012–2019. Orbis Bank Focus is the main source of data for this study. The database provides a wide coverage of cross-country listed and non-listed commercial bank data. The findings of this thesis are expected to complement those of other related studies, which mostly use sample periods prior to the introduction of the Basel III regulations in 2011 (López-Espinosa *et al.*, 2012; Adrian and Brunnermeier, 2016; Laeven, Ratnovski and Tong, 2016).

The key research questions, related methods and findings are elaborated further in three empirical chapters. These chapters are briefly explained as follows.

1.1. Bank Herding and its Determinants

The first empirical analysis, Chapter 2: "Bank Herding and its Determinants" seeks to answer whether banks do herd to increase the likelihood of a collective bailout position should default occur. Furthermore, this chapter examines whether herding is consistent with the theory of Acharya and Yorulmazer (2007) that country-level factors influence banks' herding behaviour.

In this chapter, cross-country herding measures are derived using the Granger causality test, and the LSV method based on changes in Z-score and distance-to-default. Following Billio *et al.* (2012), volatility-adjusted stock returns are used for the Granger causality test with further restriction to fit the test within the herding context. The LSV method and Granger causality test are both commonly used to detect herding and are employed in this study to capture accounting and market information respectively in testing bank herding. Therefore, providing a fuller test of the hypotheses that banks are herding and country-level factors determine herding.

Next, the measures of herding generated from both methods are regressed against the known determinants of bank herding, especially those identified in the theoretical model of Acharya and Yorulmazer (2007). These determinants include shareholder protection laws, exposure to fiscal costs, banking sector characteristics, and regulatory and supervisory quality, controlling for macroeconomic variables and depth of credit information. Least-squares dummy-variables and maximum likelihood methods are used to estimate the parameters.

The findings of this chapter suggest that banks do herd and that herding is dependent on country-specific features. Several country-level factors that are found significant in inducing herding include exposure to fiscal costs, banking sector characteristics, and regulatory and supervisory quality. However, although the results of most of the factors are consistent with the hypothesis that country-specific factors determine herding, shareholder protection laws are not. A possible explanation for why weak shareholder protection laws and in turn, greater inside ownership of banks are less relevant is that shareholders of banks with dispersed ownership also receive subsidies in the event their banks are bailed out.

1.2. Systemic Risk Implications of Bank Herding

The third chapter: "Systemic Risk Implications of Bank Herding" aims to answer whether herding poses a systemic risk. Two measures of systemic risk used in this chapter are ΔCoVaR (Adrian and Brunnermeier, 2016) and SRISK (Brownlees and Engle, 2017). In addition, two bank-level herding measures are employed using Granger causality test to capture different aspects of herding. The first measure, DGC Leader, captures the extent of herding of a particular bank by other banks in the banking system. The second, DGC Follower, captures the extent of herding of other banks by the respective bank. Following Laeven, Ratnovski and Tong (2016), individual bank vulnerabilities are measured by: (a) equity to total assets, (b) deposits to total assets and (c) loans to total assets.

The systemic risk measures are then regressed against the interactions between individual bank vulnerabilities and the herding measures. The model follows several related studies which argue that systemic risk-taking reinforces the propagation channels of systemic risk (Acharya and Yorulmazer, 2007; Farhi and Tirole, 2012; Benoit *et al.*, 2017). Accordingly, by strengthening the channels, herding is expected to amplify the effect of individual bank vulnerabilities on systemic risk.

Following de Bandt and Hartmann (2000), financial safety nets and macroeconomic factors, in addition to bank-specific characteristics, are included in the model to account for the effect of the variables on herding and systemic risk. Bank fixed effects and year fixed effects are both included to control for unobserved bank-level and time fixed effects, respectively. Within transformation and truncated regression are both used to estimate the parameters.

The findings show that herding affects systemic risk through its interactions with individual bank vulnerabilities related to funding structure and asset structure. In addition to answering the main research question, these results provide two further findings. First, the market may have expectations on bailout subsidies should banks collectively default. This evidence is consistent with the theory that the likelihood of government bailouts induces herding (Acharya and Yorulmazer, 2007; Farhi and Tirole, 2012).

Next, the results show that an idiosyncratic shock or the distress of a bank, which is followed by other banks, poses a contagion risk.[4] This is consistent with the findings of other studies that are proponents of the information-based contagion hypothesis. Moreover, it extends the evidence provided by earlier studies by showing that the

[4] Contagion or spillover risk is defined as an event where the distress of a bank, whether due to liquidity or solvency problem, or both, threaten the viability of other banks (Goodhart and Huang, 2005).

market distinguishes the banks that are more likely to trigger a spillover effect among those banks with common financial characteristics.

1.3. The Effect of Herding on the Competition and Profit of Banks

The fourth chapter: "The Effect of Herding on the Competition and Profit of Banks" aims to answer how herding affects the competition and profit of banks. To examine the effect of herding on the competition and profit of banks, ROA and ROE are both used as profit measures. In addition, consistent with the previous empirical chapter, bank-level DGC is used as a proxy for herding.

Furthermore, this study leverages the persistence of profit (POP) models, which use dynamic panel data model to explain the relationship between bank competition and performance.[5] Bank profits are regressed on their own lagged value, the interaction between both lagged profit and the herding measures, controlling for other known profit determinants. These include market structure, bank-specific characteristics and country-specific macroeconomic factors. In addition, year fixed effects are included to control for unobserved time effects. System GMM is used to estimate the parameters and to control for unobserved bank-level fixed effects and simultaneity bias.

The results show some evidence of a higher level of competition among the banks that herd compared to the rest of the industry. However, herding is desirable if the competition in the banking industry is low, allowing banks to generate excess profit to compensate for the lower profits from herding (Acharya and Yorulmazer, 2008).

[5] The rate at which competition affects excess profit in the short-run is measured by the degree of first-order autocorrelation in the time series of profit (the degree of POP). When competition among banks that herd is weak, the POP is higher than that of the industry. However, when herding increases competition, the degree of POP is lower. Further explanation on the model is provided in the third empirical chapter ("The Effect of Herding on the Competition and Profit of Banks") of this thesis.

Furthermore, the results show that the effect of herding on competition and profit is more severe for banks that are followed by other banks compared to banks that follow other banks. This suggests that larger banks may engage in price competition to maintain their market share. In addition, smaller banks that herd may use relationship lending to extract informational rent from their borrowers and partially insulate themselves from pure price competition (Boot and Thakor, 2000; Elsas, 2005).

1.4. Contributions

To the best of my knowledge, this study is the first to provide empirical evidence of the active herding of banks to increase the likelihood of a collective bailout position should default occur. Previous studies have focused more on information-based herding and herding in certain banking activities, in particular lending (Jain and Gupta, 1987; Uchida and Nakagawa, 2007). However, other studies have suggested that, in addition to the assets side, the liabilities of banks plays an important role in triggering systemic risk (Farhi and Tirole, 2012). Accordingly, the herding identified in prior empirical studies may not necessarily provide evidence of bank herding to increase the likelihood a collective bailout position should default occur. This study complements the theoretical research on active herding that poses a systemic risk (Acharya and Yorulmazer, 2007; Farhi and Tirole, 2012).

Furthermore, this study provides a contribution to the systemic risk literature by accounting for bank interconnectedness due to herding in its empirical analysis. The finding shows that most of the interactions between individual bank vulnerabilities and herding are statistically significant in explaining systemic risk variation across banks. Hence, this study complements existing empirical research on systemic risk determinants, which has tended to focus more on individual bank vulnerabilities (López-Espinosa *et al.*, 2012; Adrian and Brunnermeier, 2016; Laeven, Ratnovski and Tong, 2016).

Finally, this research contributes to the literature on herding and that on bank competition and performance by relating both issues together. In particular, this study analyses why herding remains desirable amidst the possibility of lower profits from it. Existing empirical studies on herding have tended to focus more on methods to detect herding (Jain and Gupta, 1987; Uchida and Nakagawa, 2007). In addition, research that studies the relationship between bank competition and performance has not considered herding as a factor that affects competition and profit. The integration of both streams of literature is important to provide some empirical insights into the effect of herding on the competition and profit of banks. In particular, Acharya and Yorulmazer (2007) suggest that profit deterioration could undermine herding incentives. Nonetheless, herding is observed in several cases (Barron and Valev, 2000; Uchida and Nakagawa, 2007).

Silva-Buston (2019) proposes a method to identify bank herding and its determinants. Using the residuals of the regression of marginal expected shortfall (MES), she identifies bank herding consistent with information contagion-based herding incentives (Acharya and Yorulmazer, 2008) in European banks. Instead of using residuals, this study identifies herding directly using methods proposed in the bank herding literature. This thesis also complements the empirical research of Silva-Buston (2019) by providing evidence of banks herding due to the likelihood of government bailout.

In addition, Cai *et al.* (2018) relate bank interconnectedness to systemic risk. They find, in the U.S. syndicated loan market, systemic risk from bank interconnectedness that arises due to negative externalities from diversification strategy (Wagner, 2010; Ibragimov, Jaffee and Walden, 2011). This thesis, however, focuses on systemic risk from increased interconnectedness as a consequence of banks actively engaging in herding (Acharya and Yorulmazer, 2007; Farhi and Tirole, 2012). This thesis also proposes a broader perspective of the mechanism by which banks are interconnected. In particular, instead of being limited to certain banking activities, i.e. lending, this study considers herding that involves imitation not only of bank asset allocation but also of funding strategies.

This research also suggests several policy implications in each of the relevant empirical chapters. First, the findings of the first empirical chapter ("Bank Herding and its Determinants") highlight the importance for regulators of setting up system-wide surveillance of banking risk. A system-wide perspective would allow regulators to identify systemic risk that may arise due to direct and/or indirect correlation among banks. Although from a micro perspective banks are individually reducing their risks, the likelihood of systemic risk may increase due to herding. Furthermore, in terms of financial market structure and institutional arrangement, the result highlights the importance of reducing the exposure to high fiscal costs that may arise from having an explicit deposit insurance scheme. This can be achieved, among other means, by diversifying the source of financing in bank-centric economies through financial deepening initiatives.

Next, the finding of the second empirical chapter ("Systemic Risk Implications of Bank Herding") argues that regulators could use prudential regulations to mitigate the impact of herding on systemic risk. The finding suggests that negative externalities from excessive liquidity risk and funding risk taking may not have been fully internalised through existing regulations. Hence, regulators can mitigate systemic risk by linking liquidity standards with the cross-sectional dimension of the risk.

Finally, as proposed in the third empirical chapter ("The Effect of Herding on the Competition and Profit of Banks") regulators can use competition policies to deter herding. The Basel Committee on Banking Supervision (2010) estimates that the changes in capital and liquidity brought about by Basel III would reduce economic activity by 0.08%. Accordingly, examining the possibility of alternative approaches to prudential requirement for mitigating systemic risk would be useful. The findings of the third empirical chapter also highlight the importance for countries that are proponents of the market power-stability to adopt macroprudential policy in association with microprudential policy.

1.5. Thesis Structure

An empirical assessment on herding and the country-level determinants of herding is presented in the second chapter. The third chapter investigates the systemic risk implications of bank herding. The effect of herding on the competition and profit of banks is explored in the fourth chapter, and the fifth chapter concludes. Each empirical chapter has a standalone structure. These chapters begin with an introductory section, followed by the research objectives, literature review, methodology, sample data description, empirical results, robustness checks, and a conclusion.

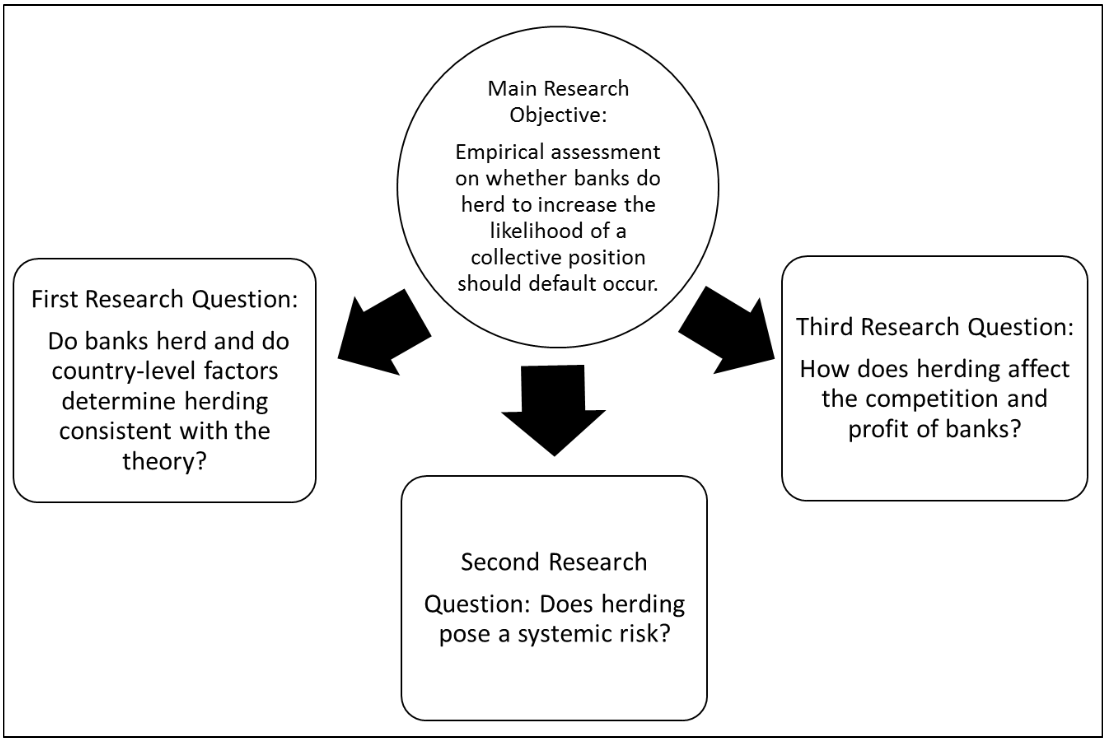

Figure 1.1 The relationship between the key research questions and the main research objective. The figure relates the three key research questions to the main research objective in this thesis. The first research question deals directly with the main objective and examines further the consistency between the herding evidence and the theory of Acharya and Yorulmazer (2007). Both suggest that several country-level factors determine herding. The second question strengthens the first by examining whether herding poses a systemic risk. The last question investigates how herding survives amidst the likelihood of profit deterioration due to herding, as suggested by Acharya and Yorulmazer (2007).

2. Bank Herding and its Determinants

2.1. Introduction

Acharya and Yorulmazer (2007) posit that the likelihood of government bailouts induces herding and banks herd to increase the likelihood of a collective bailout position should default occur. They argue herding would be observable in economies where shareholder protection laws are weak and the fiscal costs to cover a deposit insurance scheme are large. However, Perotti and Suarez (2002) provide a counter argument to herding incentives. They contend that the lending decisions of banks are a strategic substitute. Banks reduce their risky loans when the lending risk of their competitors increases so that when their rival fails, the surviving banks can acquire the failing banks. Therefore, banks are more inclined to avoid herding.

Empirical research has generated mixed evidence of herding. In particular, several empirical studies have found that smaller banks follow more informed larger banks (Barron and Valev, 2000; Nakagawa and Uchida, 2011), whereas others report weak evidence of herding. Jain and Gupta (1987) uncover evidence of only very weak herding between small banks and large banks in international lending during 1977–1982. Tran, Nguyen and Lin (2017) also point out that research related to bank concentration and competiton suggests that smaller banks may herd less as relationship lending addresses problems related to information asymmetry.

The above studies on herding focus on information-based herding and herding in certain banking activities, in particular lending. However, other research suggests that, in addition to the assets side, the liabilities side of banks plays an important role in triggering systemic risk (Allen, Babus and Carletti, 2012; Farhi and Tirole, 2012;

Agur, 2014). Accordingly, the herding identified in previous empirical studies may not necessarily provide evidence of banks herding to increase the likelihood a collective bailout position should default occur. A different measure is therefore required to identify such herding.

In addition, existing research has focused more on a single-country study. Several studies on bank herding, including Barron and Valev (2000), find evidence of herding by U.S. banks in the 1980s when they increased loans to Latin American countries; meanwhile, de Juan (2003) provides evidence of herding among Spanish banks in opening branches and Nakagawa and Uchida (2011) uncovers evidence of herd behaviour in the Japanese loan market. However, the potential influences of country-specific factors such as financial market structure and institutional arrangement on herding remains to be examined.

In summary, an empirical assessment is important to investigate whether banks do herd to increase the likelihood of a collective bailout position should default occur and whether country-specific factors induce herding. Understanding the factors that drive herding in the banking sector is important, as herding may lead to credit misallocation and inefficiency in the economy, fuel procyclicality, and trigger systemic risk (Acharya and Yorulmazer, 2007; Nakagawa and Uchida, 2011). Brown and Dinç (2011) find evidence of regulatory forbearance in a situation of too-many-to-fail in a banking sector of emerging markets and argue the possibility of similar cases in developed countries. They suggest that further research is required to explain whether the too-many-to-fail problem leads to ex-ante bank herding. This chapter aims to fill this void.

This study contributes to the discussion on herding by providing cross-country evidence that banks herd and that country-specific factors determine their herding activities. Consistent with the theoretical argument of Acharya and Yorulmazer (2007) the results of this empirical study show that exposure to fiscal costs, banking sector characteristics, and regulatory and supervisory quality affect a country's bank herding.

The results of this study suggest that smaller banks follow larger banks. Large banks are likely to be considered too-big-to-fail, as the failure of one of these banks may lead to severe impairments on the financial system (Laeven, Ratnovski and Tong, 2016). Accordingly, when one does fail, the banking sector's capacity to acquire failed banks is significantly constrained. This in turn increases liquidation costs and the likelihood of their bailouts. Hence, smaller banks are driven to herd with larger banks.

The finding is also consistent with the payoff externality hypothesis on herding. According to the hypothesis, an agent will follow the action of others if the action affects the payoffs of the respective agent. Concerning the herding of a small bank with a large one, a small bank is more inclined to herd a large bank, as when the large bank pursues a different strategy, the small bank is more likely to be acquired by the large bank when the large bank survives and the small bank fails. In addition, the small bank foregoes the likelihood of bailout subsidies in a crisis triggered by the failure of the large bank. As the size difference between the small bank and the large bank increases, the externality becomes more significant.

Furthermore, one of the findings of this chapter suggests that herding may occur even in countries where shareholder protection laws are not necessarily weak. This is possibly because even the banks with a dispersed ownership receive subsidies in the event of a joint failure. This is consistent with the argument of Brown and Dinç (2011) that, given the evidence of regulatory forbearance amidst too-many-to-fail problems in emerging markets, similar cases are also possible in developed countries.

Drawing on the evidence of empirical analysis, several policy implications under time-inconsistency bank closure policies are proposed. First, the findings highlight the importance for regulators of setting up system-wide surveillance of banking risk. A system-wide perspective would allow regulators to identify any systemic risk that may arise due to direct and/or indirect correlation among banks. Although from a micro perspective banks are individually reducing their risks, the likelihood of systemic risk may increase due to herding. The findings also highlight the importance of reducing exposure to the high fiscal costs of deposit insurance. This can be achieved, among other methods, by diversifying the source of financing in bank-centric economies through financial deepening initiatives.

This study contributes to the literature by providing cross-country analysis on herding and suggesting a broader view on the activities in which bank herd. In particular, instead of being limited to certain banking activities, herding may involve mimicking in terms of both asset allocation and funding strategies. Furthermore, this study is closest to those related to bank herding that is motivated by the likelihood of bailouts (Acharya and Yorulmazer, 2007; Farhi and Tirole, 2012). However, these studies focus on building the theoretical arguments behind the phenomenon, whereas the current study contributes to the discussion by providing an empirical assessment of the proposed theory.

Silva-Buston (2019) reports evidence consistent with information contagion-based herding incentives. Herding in her study is measured by the residuals of the regression of Marginal Expected Shortfall (MES) (Acharya *et al.*, 2017) on a measure of systematic MES. However, this chapter measures herding directly using methods similar to those proposed in existing bank herding literature and focuses on herding motivated by the likelihood of government bailouts.

2.2. Research Objectives

The key objectives of this chapter are to investigate (a) whether banks do herd to increase the likelihood of a collective bailout position should default occur and (b) whether country-specific factors induce such herding. Regarding objective (a), this chapter attempts to provide an empirical assessment on whether banks do herd to increase the likelihood of a collective bailout position should default occur. Acharya and Yorulmazer (2007) posit that banks herd by lending to the same industry. Perotti and Suarez (2002), however argue that banks' investment decisions are a strategic substitute. Hence, banks are less inclined to herd. An empirical study is therefore required to examine whether banks do herd.

Regarding objective (b), this chapter aims to investigate whether shareholder protection laws, exposure to fiscal costs, banking sector characteristics, and regulatory and supervisory quality affect herding. An empirical analysis on the relationship between herding and the aforementioned country-specific factors would allow policymakers to obtain more comprehensive information on herding and connect the issue with policies related to the banking sector and crisis prevention.

2.3. Literature Review

2.3.1. What is Herding?

Bikhchandani and Sharma (2000) define herding as a behaviour in which an agent intentionally or actively mimics the behaviour of other agents. This behaviour is different from unintentional or spurious herding in which agents, given an identical set of information, provide a similar and simultaneous response to a common factor (e.g. macroeconomic condition). For example, in periods of solid economic growth and expansionary monetary policy, spurious herding in lending activity may arise. Banks may collectively and simultaneously provide loans to economics sectors that contribute most to the growth.

However, the main concept of active herding is that other agents' behaviour influences the social learning[6] of the agent observing the signals (Vives, 1996). Hence, active herding is not spurious and is driven by non-fundamental factors such as information cost, the agency problem and payoff externality. The presence of active herding may lead to inefficiency in the economy, as banks forgo profitable loans in other sectors of the economy. At the same time, the behaviour may also pose a systemic risk when it increases the likelihood of a collective bailout position should default occur (Acharya and Yorulmazer, 2007; Nakagawa and Uchida, 2011).

2.3.2. Herding Models

According to Devenow and Welch (1996), there are two different models of herding: 1) irrational or near-rational herding, and 2) rational herding models. Irrational herding models emphasise investor psychology to explain herding. In this

[6] As defined by Vives (1996), social learning is the process in which an agent learns about the private information of other agents in the society by observing the actions of the other agents.

type of herding, an agent follows other agents without rational analysis. Near-rational herding models assume agents use a heuristic process to collect and process information and, hence, generate sub-optimal decisions. However, rational herding models focus on inefficiencies, in which information cost or incentive issues distort optimal decision-making.

Although the use of irrational or near-rational herding models to explain herding phenomena is gaining more prominence, this research uses rational herding models to explain whether the too-many-to-fail phenomenon can lead to herding in the banking sector. This approach is consistent with the theoretical framework of Acharya and Yorulmazer (2007) that assumes agents are rational. Hence, the discussion in this chapter is focused on rational herding.

2.3.3. Existing Hypotheses on Rational Herding

Devenow and Welch (1996) suggest there are three main hypotheses to explain rational herding: 1) the informational learning or cascade hypothesis; 2) the principal–agent or reputational concern hypothesis; and 3) the payoff externality hypothesis.

1. Informational Learning

Informational learning or cascades occur when agents find it difficult or costly to assess information on investments. To mitigate the problem, agents incorporate the actions of other agents into their investment decision (Banerjee, 1992; Avery and Zemsky, 1998; Bikhchandani, Hirshleifer and Welch, 1998). The cascade model applies in a context in which agents face similar investment decisions and have private but imperfect information regarding the prospect of the investment. The agent, however, can make inferences on the quality of the investment by observing the action of others. Because the value of the inference improves as more agents make the same investments, the observing agent at a certain point follows the herd, disregarding their own private information.

It is important to distinguish this type of herding from irrational herding. The latter occurs when agents passively mimic others' actions. However, the former occurs because of observational learning among agents. Hence, rational observant agents consider not only the presence of herding but also the factors driving the herd. Consequently, this type of herding is fragile to the arrival of adverse information.

Studies on informational cascades in the banking literature includes that of Chang *et al.* (1997), which examines the geographical concentration of bank branches in New York City during 1990–1995. Based on their study, banks' decisions to expand their branches depend on the number of branches operating within a certain area. This behaviour is driven by banks having imperfect information on the business prospect of opening a new branch. Furthermore, Barron and Valev (2000) show that small banks – which are assumed to have less wealth – would rather follow large banks, which are assumed to have sufficient wealth to invest in research. Because of their wealth, large banks have the comparative advantage of extracting information on risky investments compared to small banks.

Nakagawa and Uchida (2011) find evidence of herding among Japanese banks. According to their study, regional banks with less informational advantage on loans imitate the lending decisions of city banks. In addition, city banks mimic those of long-term credit banks and trust banks, in which both banks are considered to have better lending information. Moreover, their cross-sector analysis shows that herding occurs in loans provided to emerging industries, in which banks are more uncertain about the prospects of their new borrowers. This evidence supports the informational learning hypothesis.

2. *Principal–Agent Problem or Reputational Concern*

Rational herding can also emanate from the principal–agent problem. According to Scharfstein and Stein (1990), this type of herding arises when the principal has imperfect information on the agent's skill and the agent's performance is evaluated based on relative instead of absolute measures. This form of evaluation is common in practice. Morck, Shleifer and Vishny (1988) document that the dismissals of senior management are related to relative performance of the company compared to its industry rather than the absolute performance of the company itself. Accordingly, when the market has asymmetric information on management skill, managers mimic each other's actions to avoid being considered as poor skilled and, hence, to preserve their reputation.

One of the studies considered seminal in this area is that of Scharfstein and Stein (1990). This study provides a model that proposes an optimal equilibrium in which each agent prefers to mimic the actions of others due to concerns on how the labour market perceives their ability. Neither the agents nor the market knows which agents have good or bad skills. The market makes inferences on the agents' skills based on the agents' investment decisions, in particular whether the decisions are similar or different to one another. Subsequently, the market updates their belief based on the investment return. Managers' compensation is based on the market's perception of their skill. It is assumed high-skilled managers will observe identical private information regarding the investment project. However, low-skilled managers observe independent noise. Although this behaviour is inefficient from a social welfare perspective, it is rational from the perspective of the agents who are concerned about their reputations in the labour market.

In the banking literature, Rajan (1994) develops a model in which, in addition to maximising bank's earnings, managers are concerned about the stock or labour market's perception of the managers' skill. This provides incentives for managers to conceal the actual size of their non-performing loans to enhance their earnings. In an adverse economic condition, all banks perform poorly and set provisions on their bad loans. When sufficient numbers of banks are making the same decisions, poor-quality managers imitate the decisions of good-quality managers, setting provisions on their ex-ante bad loans without being noticed. As evidence of his hypothesis, Rajan (1994) uses the New England crisis of the early 1990s. He finds that loan loss provisions of New England banks from 1986–1992 are significantly related to the average provisions taken by other New England banks.

Rajan (1994) highlights two main differences between the reputational concern hypothesis and the informational learning hypothesis. First, unlike the later hypothesis that assumes agents are relatively uninformed and rely on other agents to obtain information, the former assumes agents hold information on the true condition of their investment. Consequently, the informational learning hypothesis predicts far less persistence of herding after the true state is revealed. However, the reputational concern hypothesis argues that agents are able to exit the investment only after the market receives common negative signals on the investment.

3. Payoff Externality

The payoff externality hypothesis involves herding that arises when the action of an agent affects the payoffs of others. In the banking literature, payoff externality is commonly used to explain the run-on-the bank phenomenon and arises due to the sequential service constraint inherent in demand deposits.

One of the studies considered seminal in pure-panic bank runs is that of Diamond and Dybvig (1983). In their model, the consumption needs of depositors are assumed uncertain and the liquidation of long-term investments incurs costs. Furthermore, depositors are willing to deposit their funds in a bank if the bank provides insurance for their idiosyncratic liquidity needs. A good equilibrium is attained when all depositors believe others are withdrawing their funds according to their consumption needs. Therefore, the bank can meet the withdrawals without having to liquidate its long-term assets. However, a bad equilibrium arises when depositors believe others are terminating their demand deposit contract earlier. Under such conditions, it would be rational for depositors to follow the herd and liquidate their contract to avoid being the last to withdraw and incur loss from the liquidation of the long-term assets.

Concerning bank herding, Acharya and Yorulmazer (2007) show that bank closure policies are exposed to the too-many-to-fail concern: when a large number of banks default, the bailout of some or all banks are ex-post optimal. Furthermore, when banks are bailed out, the owners enjoy subsidies in the form of ownership preservation. The subsidy is granted to avoid excessive risk taking and corporate expropriation by insiders due to common shareholder dilution as a result of capital injection. Accordingly, banks have the incentive to follow others to increase the likelihood of a collective bailout position should default occur. In addition, Acharya and Yorulmazer (2007) posit that herding is more prevalent in economies with weaker shareholder protection laws and exposure to high fiscal costs of deposit insurance.

The study also examines the case in which two banks are asymmetric in term of size, one large and one small. Following the default of the small bank, the large bank can purchase the small bank at a discount. Furthermore, when both banks fail, the bailout subsidies do not increase for the large bank. However, they increase for the small bank. This generates a payoff externality for the small bank. In particular, when the large bank takes a different lending strategy compared to the small bank, the former can purchase the latter at a discount when the latter fails. The latter bank would also forego bailout subsidies, because both banks are less likely to fail collectively. Accordingly, the small bank would prefer to herd to increase the likelihood of bailout subsidies, instead of being acquired at a discount, when it fails. However, the large bank would prefer to distinguish itself from the small bank because the bailout subsidies do not increase for the large bank. This suggests that the too-many-to-fail problem is more relevant for smaller banks and the too-big-to-fail problem is more relevant for larger banks.

Acharya and Yorulmazer (2008) emphasise herding may arise from a coordination game instead of the outcome of an informational cascade. Consistently, instead of sequential, herding in their study is a simultaneous decision of banks aimed at coordinating correlated investments.

2.3.4. The Gap in the Literature and the Contributions

1. ***Trade-off between Profit Maximisation and Herding Incentive***

The payoff externality hypothesis suggests that an agent will follow the action of other agents if the action affects the payoffs to the respective agent. In the case of bank runs, an uninformed depositor observing a large number of withdrawals would cash in their deposits to avoid being the last depositor to do so and incur loss due to the premature liquidation of the bank's long-term assets.

Concerning the herding model developed by Acharya and Yorulmazer (2007), banks' decisions to follow others increases the likelihood of a collective bailout position should default occur and their bailouts. This reduces the incentive for a small bank to differentiate itself. In particular, when the failure is due to idiosyncratic shock, the bank is likely to be acquired by the surviving banks at a discount. It also foregoes bailout subsidies under a collective default.

Nonetheless, unlike the depositors in bank runs, the bank faces a trade-off by imitating the action of others. In particular, profit is likely to deteriorate as loan competition in certain sectors increases due to herding. Acharya and Yorulmazer (2007) raise this issue, arguing that profit deterioration could undermine herding incentives in their model.

Acharya and Yorulmazer (2007) propose alternative mechanisms to achieve herding in which profit deterioration can be avoided. One is through inter-bank loans, hence, exposing the banking sector to a contagion-type phenomenon. The mechanism, however, may not necessarily lead to systemic risk. Ahnert and Georg (2018) argue that information spillover, arising from counterparty risk, moderates the possibility of joint defaults. As a response to information contagion, banks make more conservative ex-ante decisions, choosing to reduce counterparty risk and hoard liquidity. Accordingly, an empirical assessment of the theory proposed by Acharya and Yorulmazer (2007) is required to establish whether banks do herd amidst the possibility of profit deterioration.

2. *Evidence of Bank Herding*

Empirical research has generated mixed evidence of herding. In particular, several studies have found that smaller banks follow more informed larger banks (Barron and Valev, 2000; Nakagawa and Uchida, 2011). However, others find weak evidence of herding. Jain and Gupta (1987) empirically test whether a group of small banks followed large banks in international lending during 1977–1982. During that period, neither the borrowers nor the lenders had adequate experience in determining the optimal levels of debt for an economy or country exposures. In addition, it was both difficult and costly to collect and process information on any specific country. Hence, many observers believe banks were herding by mimicking each other's lending decisions to deal with asymmetric information problems. Nonetheless, based on their study, Jain and Gupta (1987) find only very weak herding between smaller and larger banks.

In addition, Tran, Nguyen and Lin (2017) point out that research related to bank concentration and competition suggests that smaller banks may herd less, as relationship lending addresses problems related to information asymmetry. More precisely, Berger and Udell (2002) argue that small businesses are less transparent and have limited financing sources compared to large firms. Hence, banks providing loans to these businesses often depends on relationship lending, in which small banks have a comparative advantage, to acquire soft information on the borrower. The argument is consistent with that of Carter, McNulty and Verbrugge (2004), who find that large banks in the U.S. tend to provide loans to larger, creditworthy, transparent borrowers based on hard information. However, small banks tend to provide loans to smaller, riskier and less transparent borrowers based on soft information. In addition, a cross-country study by Berger, Hasan and Klapper (2004) also finds a similar result, suggesting that small banks tend to specialised in small-to-medium enterprise (SME) loans. In particular, they find that the total market share of small banks is related to, among others, a higher presence of SME.

3. Broader Measure of Herding

Much of the research related to herding has focused on information-based herding and herding in certain banking activities, in particular lending (Jain and Gupta, 1987; Barron and Valev, 2000; Uchida and Nakagawa, 2007). Therefore, the methods used in these studies may be of limited use for identifying herding that increases the likelihood of a collective bailout position should default occur.

More precisely, several studies have suggested that, in addition to the assets side, the liabilities side of banks plays an important role in triggering systemic risk. Allen, Babus and Carletti (2012) propose a model in which the interaction between asset commonality and short-term debt of banks may trigger systemic risk. According to their model, a set of banks may hold similar asset portfolios due to the limited number of assets available. Nonetheless, when the portfolios are financed using long-term debt, the likelihood of a collective default from asset commonality is lower compared to when they are financed using short-term debt.

The argument that bank liabilities are also important in leading to joint failures is also supported by Agur (2014). He suggests that lowering correlation among bank portfolios does not necessarily reduce funding vulnerability from the wholesale market for banks. However, banks could reduce funding risk by increasing the portion of their retail deposits. Tasca, Mavrodiev and Schweitzer (2014) also show that, although banks can reduce investment loss through asset diversification, leverage plays a more critical role in determining banks' default risk.

Farhi and Tirole (2012) provide a similar argument. Because of the likelihood of government bailout when banks default collectively, they are driven to herd by engaging in collective maturity mismatch. Hence, their theory supports the argument that bank liabilities play an important role in triggering systemic risk. It also complements the theory of Acharya and Yorulmazer (2007) that banks herd to increase the likelihood a collective bailout position should default occur.

Recent empirical studies on banking stability have incorporated the correlated risk taking behaviour of banks in their model and control for herding. Beck, De Jonghe and Schepens (2012) study the effect of bank competition on bank stability. As the dependent variable, they use individual bank Z-score. Furthermore, to control for herding, they use three variables: 1) the aggregate Z-score, which measures the country level Z-score; 2) activity restrictions, which measures the extent banks are prohibited from activities related to securities, insurance and real estate; and 3) heterogeneous bank revenues, which measures whether there are significant revenue differences among banks.

Anginer, Demirguc-Kunt and Zhu (2014a) study the relationship between the correlated risk-taking of banks and competition. To measure risk correlation, they propose the total variation of changes in the default probability of a given bank, explained by changes in the default probability of other banks. They also use activity restrictions to control for herding, similar to Beck, De Jonghe and Schepens (2012). The above approaches, however, are not necessarily sufficient to suggest the presence of active herding. In particular, the statistical significance of the variables they use to control herding may also capture spurious herding, i.e. homogenous bank revenues related to business cycle trends or correlated risk from simultaneous response to activity restrictions.

Silva-Buston (2019), studying the effect of competition on systemic risk, proposes bank herding as a channel that explains the relationship between competition and systemic risk. She identifies herding using excess systemic risk as proxy for interbank commonality that is not driven by diversification strategies. The variable is measured by the residuals of the regression of the MES (Acharya *et al.*, 2017) on a measure of systematic MES. However, several studies have criticised the use of residuals as proxies, arguing that residual regression may lead to biased parameter estimates, especially when correlations exist between the independent variables (Freckleton, 2002; Chen, Hribar and Melessa, 2018).[7] Moreover, excess systemic risk, as Silva-Buston (2019) proposes, may also capture the effect of factors other than herding on systemic risk, hence exposing the proxy to measurement error.

4. Cross-Country Study

Existing empirical research on bank herding tends to focus more on a single country. These studies include Barron and Valev (2000), who find small U.S. banks follow large banks with regard to which countries to lend to during the period 1982–1994; de Juan (2003), who provides evidence of herding among Spanish banks in opening branches; and Nakagawa and Uchida (2011), who find evidence of herd

[7] The common procedure of studies that use residuals as dependent variables is to first use OLS to decompose a dependent variable into its predicted and residual components. Next, the residual from the first regression is used as the dependent variable in the second regression to test hypothesis on its determinants. Studies using this procedure often do not include the independent variables from the first regression as additional independent variables in the second regression. According to Freckleton (2002) and Chen, Hribar and Melessa (2018), the two-step procedure generates biased estimates of the second-step regressors when correlation exist between the independent variables in the first regression and those in the second regression.

behaviour in the Japanese loan market. Hence, country-specific factors such as financial market structure and institutional arrangement that may affect herding are not separated in the existing research. A cross-country study enables the analysis of these factors, in particular whether country-specific factors affect herding. Hence, further investigation on the relationship between these factors and herding would contribute to the current discussion on herding.

5. *Contributions to Existing Literature*

As discussed above, although there are some studies on bank herding, there are still important gaps in the literature. This study aims to fill the void in the literature by addressing the following gaps:

1. The model developed by Acharya and Yorulmazer (2007) to explain the too-many-to-fail phenomenon does not account for profit deterioration due to banks' lending to similar industries. Perotti and Suarez (2002) also provide a counter argument to herding incentives, arguing that the lending decisions of banks are a strategic substitute instead of strategic complementary. Several empirical studies have also generated mixed evidence of bank herding. Both, the contradictory theoretical views related to bank herding and the mixed evidence in prior empirical research, motivate the empirical investigation of this study on whether banks do herd to increase the likelihood of a collective bailout position should default occur.
2. Most of the current studies have emphasised information-based herding and herding in certain banking activities, in particular lending. However, several studies have suggested that, in addition to the assets side, the liabilities side of banks also play an important role in triggering systemic risk. Accordingly, the

herding identified in previous empirical studies may not necessarily provide reliable evidence of banks herding to increase the likelihood of a collective bailout position should default occur. This study attempts to improve the bank herding measure used in prior research by taking a broader perspective on the activities in which bank herd.

3. Existing studies tend to focus on a single-country study. Hence, country-specific factors are not accounted for. However, Acharya and Yorulmazer (2007) suggest that several country-specific characteristics may affect herding. Hence, this chapter provides a cross-country study to investigate whether country-specific features induce herding behaviour.

Silva-Buston (2019) proposes a method to identify bank herding and its determinants. To measure herding, Silva-Buston (2019) proposes the residuals of the regression of MES (Acharya *et al.*, 2017) on a measure of systematic MES. However, this chapter aims to measure herding directly using methods proposed in the bank herding literature. Furthermore, using European bank-level data, Silva-Buston (2019) finds herding consistent with information contagion-based herding incentives.[8] Therefore, this study complements her research. In particular, Acharya and Yorulmazer (2008) argue that herding due to the likelihood of government bailouts complements that in response to information spillover.

[8] Acharya and Yorulmazer (2008) show that the increase in a bank's cost of borrowing due to information spillover is lower when the bank has common risk exposure with other banks. Therefore, banks herd to minimize the effect of information contagion on the expected cost of borrowing.

2.4. Data and Variables

2.4.1. Sample

Herding measures can be misleading when a country only has a few banks in the sample. For example, when a country has only two banks in the sample, the LSV measure may indicate that 50% of the banks in the respective country are increasing their risk when only one of the two banks in the sample is doing so. The problem may become more significant when the sample is limited only to listed banks due to market data requirements. Hence, to improve the representativeness of the country-level data, countries are required to have a minimum number of banks in the sample.

The decision concerning the adequate number of banks is arbitrary. Nonetheless, several existing studies have proposed a certain threshold level. This study follows the country-level data requirement set by Berger *et al.* (2009). In particular, they require a country to have at least five active banks included in their sample. The size restriction is also close to that used by Anginer, Demirguc-Kunt and Zhu (2014a), which excludes countries with fewer than seven banks. Accordingly, the total number of unbalanced panel data that are consistent with the criteria is presented in Table 2.1.

This study proposes several herding measures, covering the same 5-year observation period (2012–2016). The Z-Score LSV measure uses the largest data sets (314 country-year sample), covering 129 countries and 6,889 banks. However, DD LSV and DGC measures use a 245 and 241 country-year sample, covering 53 and 51 countries and 575 banks and 615 banks respectively. As market data are required to compute both measures, the sample covers only listed banks and, hence, the sizes of the samples are not as large as that for the Z-Score LSV.

In addition, the difference in the sample size between DD LSV and DGC is due to differences in the availability of observations of different components required to compute the measures. In particular, DD LSV uses distance-to-default as the risk measure for herding, whereas DGC is based on volatility-adjusted stock return.

The herding measures and the method used to derive these measures are explained in the subsequent section.

2.4.2. Herding Measures

Several herding measures are proposed to provide a fuller test of the hypotheses that banks are herding and country-level factors determine herding: LSV based on changes in Z-score (Z-Score LSV), LSV based on changes in distance-to-default (DD LSV) and DGC. These measures are complementary to each other as the Z-Score LSV is based on accounting data, whereas DD LSV and DGC both use stock returns that capture market information.[9] In addition, Z-Score LSV does not capture the off-balance sheet exposure of banks. However, DD LSV and DGC both use market information, assuming in efficient markets that current stock prices reflect information related to the financial institutions (Krainer and Lopez, 2004; Gropp, Vesala and Vulpes, 2006), including off-balance sheet exposures.

These measures are derived using two different methods that are commonly used to detect herding: Lakonishok, Shleifer and Vishny (LSV) and Granger causality test. The next two sections discuss in more detail each of the measure and the method used to generate the measure.

[9] Similarly, Silva-Buston (2019) uses the residuals of the regression of MES, which is computed using stock return, to identify bank herding. Instead of using residuals, bank herding in this study is measured directly using the Granger causality test.

1. Lakonishok, Shleifer and Vishny

The LSV method is developed by Lakonishok, Shleifer and Vishny (1992) to measure the extent to which funds herd in equity investment. The technique is subsequently adopted by Uchida and Nakagawa (2007) to investigate whether Japanese banks herd in the domestic loan market. To detect herding in the respective market, LSV is computed based on whether the proportion of banks that increase or decrease their loans outstanding within a certain industry deviates significantly from the country-level loan trend.

This chapter argues that to increase the likelihood of a collective bailout position should default occur, banks need to synchronise their asset allocation and funding strategies. This in turn causes the risk characteristics of these banks to become similar. Accordingly, LSV in this study measures the deviation of the proportion of banks whose risk increases within a single country from the global trend in bank risk:

$$LSV_i = |P_i - P_t| - E|P_i - P_t| \qquad (2.1)$$

Where P_i denotes the proportion of banks that increase their risk in country-year i. P_i is calculated as:

$$P_i = \frac{X_i}{N_i} \qquad (2.2)$$

Where N_i denotes the number of banks in country-year i and X_i denotes the number of banks whose risk measure deteriorates in country-year i.

Furthermore, P_t denotes the global trend in bank risk or the expected proportion of banks globally whose risk increases in year t:

$$P_t = \frac{\sum_{i=1}^{k} X_i}{\sum_{i=1}^{k} N_i} \qquad (2.3)$$

In equation (2.1), the expected deviation $E|P_i - P_t|$ is subtracted from $|P_i - P_t|$ to normalised LSV. $E|P_i - P_t|$ is calculated based on the assumption that the distribution of a random value of $|P_i - P_t|$ follows a binomial distribution:

$$E|P_i - P_t| = E[|P_i - P_t|;\ X_i \sim B(N_i, P_t)] \qquad (2.4)$$

$$E|P_i - P_t| = \sum_{X_i=0}^{N_i} |P_i - P_t| \times C_{X_i}^{N_i} \times [P_t]^{X_i} \times [1 - P_t]^{N_i - X_i} \qquad (2.5)$$

and

$$C_{X_i}^{N_i} = \frac{N_i!}{X_i!\,(N_i - X_i)!} \qquad (2.6)$$

As in Uchida and Nakagawa (2007), a chi-square test is used to test the statistical significance of herding within a country, with the following test statistics:

$$Z_i^2 \equiv \frac{(P_i - P_t)^2}{P_t(1 - P_t)/N_i} \sim \chi^2_{(1)} \text{ under the null hypothesis of no herding} \qquad (2.7)$$

A significance level of 5% is used in the test.

Therefore, the test reduces the probability of type 1 error, in particular, that of having to suggest a high Z_i^2 value as an indication of herding within a country when it is not true or spurious.

Two commonly used individual bank risk measures employed in this study as the underlying variable by which banks herd are: Z-score and distance to default. The Z-score is an accounting based bank risk measure, which is commonly used in the literature related to financial stability. The measure is calculated as:

$$Z_{i,t} = \frac{ROA_{i,t} + (E/TA)_{i,t}}{\sigma ROA_{i,t}} \qquad (2.8)$$

Where *ROA* denotes the mean return on assets, *E/TA* denotes the equity to total assets, *σROA* denotes the standard deviation of ROA, *i* and *t* the notation for bank i and time t. Following Beck, De Jonghe and Schepens (2012), a three-year rolling window is used to calculate the average and standard deviation of ROA. The Z-score is inversely related to the probability of bank solvency problem. Furthermore, data on ROA and the equity-to-total-assets ratio are obtained from Orbis Bank Focus.

The second measure, the distance to default, was originally developed by Merton (1974). Although the model was initially used to predict bankruptcy in the non-financial sector, Merton (1977a, 1977b) suggests the applicability of the model to price deposit insurance in the banking context. Consistently, the model has been commonly used to measure commercial banks' default risk.

The model is calculated as:

$$V_E = V_A e^{-rt} N(d_1) - De^{-rt} N(d_2) + (1 - e^{-rt}) V_A \qquad (2.9)$$

$$d_1 = \frac{\ln(\frac{V_A}{D}) + (\hat{r} - \delta + \frac{\sigma_A^2}{2})}{\sigma_A \sqrt{t}};\ d_2 = d_1 - \sigma_A \sqrt{t} \qquad (2.10)$$

Where V_E denotes the market value of common equity; V_A the market value of asset; D the notation for the face value of debt, using total liabilities as a proxy; $\hat{r}$ the expected return; δ the dividend rate expressed in terms of V_A; σ_A the standard deviation of assets; and t equals 1 year. Distance-to-default is inversely related to bank default risk.

Furthermore, as data on V_A, $\hat{r}$ and σ_A are not available, following Fu, Lin and Molyneux (2014), the method proposed by Bharath and Shumway (2008) is used to generate these variables:

$$V_A = V_E + D \qquad (2.11)$$

$$\sigma_A = \frac{V_E}{V_A}\sigma_E + \frac{D}{V_A}\sigma_D \qquad (2.12)$$

$$\sigma_D = 0.05 + 0.25\sigma_E \qquad (2.13)$$

$$\hat{r} = r_{t-1} \qquad (2.14)$$

Where σ_E denotes the standard deviation of daily equity returns over the past year multiplied by the square root of the average number of trading days in the year (set at 252 trading days). In addition, r_{t-1} is calculated by cumulating daily returns over the previous year. Furthermore, the expected return is replaced with the risk-free rate when the former is negative. The 1-year treasury constant maturity rate obtained from the Board of Governors of the Federal Reserve System is used as the risk-free rate.

Furthermore, Merton's distance-to-default (*dd*) is calculated as:

$$dd = \frac{\ln\left(\frac{V_A}{D}\right) + \left(\hat{r} - \delta - \frac{{\sigma_A}^2}{2}\right)t}{\sigma_A\sqrt{t}} \qquad (2.15)$$

Related data on bank total liabilities and total equity are obtained from Orbis Bank Focus. Furthermore, data on individual banks' daily stock returns and price to book value are obtained from Datastream. In addition, dividends are calculated as the difference between net income and retained income data from Orbis Bank Focus.

2. *Degree of Granger Causality*

The linear Granger causality method is proposed by Billio *et al.* (2012) and, in this study, the method is used to derive a measure of herding. The method tests whether a shock in a financial institution leads to a shock in another financial institution.[10]

Granger's procedure is to run a regression of the form:

$$\tilde{R}_{i,t} = \sum_{p=1}^{n} \alpha_i \tilde{R}_{i,t-p} + \sum_{p=1}^{n} \beta_{i,j}\, \tilde{R}_{j,t-p} + \varepsilon_{i,t} \qquad (2.16)$$

$$\tilde{R}_{j,t} = \sum_{p=1}^{n} \alpha_j\, \tilde{R}_{j,t-p} + \sum_{p=1}^{n} \beta_{j,i}\, \tilde{R}_{i,t-p} + \varepsilon_{j,t} \qquad (2.17)$$

[10] Billio *et al.* (2012) find that the linear Granger causality method is robust to contemporaneous common shocks. As a robustness check, they use stock market return to control for common-factor exposure in the Granger causality test. They report similar results with the main test, which do not use the variable.

Where $\tilde{R}_{i,t-p}$ denotes the adjusted stock return measure of bank *i* at time *t* - *p*, $\tilde{R}_{j,t-p}$ the adjusted stock return measure of bank *j* at time *t* - *p*, where $i \neq j$, $\varepsilon_{i,t}$ and $\varepsilon_{j,t}$ are two uncorrelated white noise processes. Accordingly, i follows j when $\beta_{i,j}$ is different from zero. Schwarz Bayesian information criterion is used as the model-selection criteria to determine the optimal lag *p*.

The method uses volatility-adjusted stock return as the dependent variable in equation (2.16) and (2.17) to control for heteroscedasticity. In particular:

$$\tilde{R}_{i,t} = \frac{R_{i,t}}{\hat{\sigma}_{i,t}} \qquad (2.18)$$

Where $\tilde{R}_{i,t}$ denotes the adjusted stock return measure of bank *i* at time *t*, $R_{i,t}$ is the stock return for bank *i* at time *t* and $\hat{\sigma}_{it}$ is the notation for the estimated volatility predicted with a GARCH(1,1) model.

Following Billio *et al.* (2012), commercial banks are required to have at least 36 pieces of data of monthly stock returns within a 5-year observation period to be included in the sample. In addition, to better reflect adequate market information, banks with shares that are inactively traded or where there is no single price movement within the length of the observation are excluded from the sample.

To measure the extent of connectedness between the commercial banks within a country, the degree of Granger causality (DGC) is used. The measure is defined as the fraction of statistically significant $\beta_{i,j}$ among all $N(N-1)$ pairs of N financial institutions:

$$DGC \equiv \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j \neq i} (j \rightarrow i) \qquad (2.19)$$

Although the purpose of the linear Granger causality method proposed by Billio *et al.* (2012) is to measure the direction and the extent of connectedness between financial institutions, the Granger causality test was initially developed by Granger (1969). The method is commonly used to test the herding hypothesis in the banking sector (Jain and Gupta, 1987; Barron and Valev, 2000; Nakagawa and Uchida, 2011).

Consistently, to further fit the linear Granger causality method within the context of herding, a more restrictive approach, a one-way Granger causality test, is proposed. Jain and Gupta (1987) argue that a one-way test reduces the possibility of identifying spurious herding as active herding. In particular, they argue that the two-way test may indicate several possibilities: (i) a feedback effect in which both banks consider each other's behaviours when making lending decisions, and (ii) the lending or investment decisions are the result of similar credit or business analysis approach. The latter, however, does not necessarily indicate the existence of herding behaviour.

In this test, the one-way DGC is defined as the fraction of statistically significant $\beta_{i,j}$, excluding those with feedback relationships, among all $N(N-1)$ pairs of N financial institutions. A significance level of 5% is used in both tests. Data on individual bank's monthly stock returns are sourced from Datastream.

2.4.3. Determinants of Bank Herding

Acharya and Yorulmazer (2007) theorise as to why herding would be more severe in a country. They suggest several country-specific factors that are considered as determinants of herding. In particular, they argue that herding is more prominent in countries where shareholder protection laws are weak and exposure to fiscal costs to cover deposit insurance scheme is large.

In addition to both factors, two related variables that may affect herding are considered: 1) banking sector characteristics and 2) regulatory and supervisory quality. A detailed explanation of each variable is provided in the following discussion.

1. Shareholder Protection Laws

Acharya and Yorulmazer (2007) suggest that bailout subsidies are higher in countries where agency problems, such as expropriation of corporate resources by bank owners, are more severe. In such countries, regulators are less likely to dilute the equity share of the bank owners when the respective banks are bailed out to avoid the problem.

Furthermore, according to Caprio, Laeven and Levine (2007), inside ownership and state ownership of banks are more commonly observed compared to dispersed ownership in countries with weaker shareholder protection laws. This is because weaker shareholder protection laws imply a higher risk of fraud by insiders and larger inside ownership is expected to prevent such problem. Therefore, this study hypothesises that herding is negatively related to the strength of shareholder protection laws within a country.

The strength of shareholder protection is measured by the strength of minority investor protection index, which is acquired from the World Bank Ease of Doing Business annual database. The index is the average of the extent of disclosure index; the extent of director liability index and the ease of shareholder suits index; a higher value indicating a stronger investor protection. Furthermore, a dummy variable is included to indicate changes in the method used to measure the index. In particular, after 2013, the index also covers the extent of governance index. The index includes the extent of shareholder rights index, the extent of ownership and control index, and the extent of corporate transparency index.

2. Exposure to Fiscal Costs

Acharya and Yorulmazer (2007) posit that time-inconsistency in bank liquidation policies or too-many-to-fail problems are more observable in economies where fiscal costs of bailouts are significant.[11] In particular, when fiscal costs are large, the cost of ex-ante committing to liquidate banks is low because liquidation is not always costly compared to a bailout. This leads to time-inconsistency in bank closure policies. Although it is ex-ante optimal for regulators to commit to bank liquidation, they find it ex-post optimal to bailout banks when a large number of them fails. Furthermore, fiscal costs arise due to government funding to pay off failed deposits, net of any proceeds from bank liquidation. Hence, countries with explicit deposit insurance are more exposed to fiscal costs.

This study hypothesises that herding is positively related with the existence of deposit insurance coverage. An explicit deposit insurance scheme is defined as the existence of an explicit deposit insurance scheme within a country. A dummy variable is created and set equal to 1 if a country has an explicit deposit insurance scheme and is set to 0 otherwise. Explicit deposit insurance scheme data are collected from the World Bank Deposit Insurance database. The database was published in 2015 with data dated as of end 2013.

Acharya and Yorulmazer (2007) argue that when the banking sector is relatively large compared to the rest of the economy, problems in the sector and bank bailouts

[11] Fiscal costs of bailouts are opportunity costs from not receiving any proceeds from bank sales or liquidation. Regulators incur the costs when they decide to bailout the failing banks instead of liquidating them.

are more related to high fiscal costs. In such a case, a country would need to raise its taxes to generate the necessary funds. It may also borrow or issue bonds to meet the funding requirement. Eventually, the higher debt level would increase the country's borrowing costs, leading to higher taxes to pay for the additional costs.

In addition, in these countries, adverse conditions in the banking sector are more likely to impose larger social welfare losses on the economy (Acharya and Yorulmazer, 2007). Hence, the costs of liquidating too many banks would be higher and the government is more likely to seek a bailout as an alternative approach.

This study hypothesises that herding is positively related to the significance of the banking sector as a financing source within a country. The significance of the banking sector is measured by banking sector total assets and the availability of off-shore financing for non-financial corporation. The inclusion of the latter variable is also consistent with the findings of Dell'Ariccia, Detragiache and Rajan (2008) that the effects of banking crises are stronger in countries with less access to foreign finance. Furthermore, banking sector total assets is measured in natural logarithm and alternative source of financing is measured by the size of non-financial corporation international debt securities outstanding to nominal GDP.

Data on banking sector total assets are obtained by aggregating individual bank size data from Orbis Bank Focus. In addition, the size of non-financial corporation international debt securities outstanding data are retrieved from the Bank for International Settlements Debt Securities Statistics as of December 2017 and nominal GDP are obtained from the International Monetary Fund World Economic Outlook database as of October 2017.

3. Banking Sector Characteristics

In a banking system consisting of one large and one small bank, Acharya and Yorulmazer (2007) show that the small bank has an incentive to follow the large bank. This is because when the large bank pursues a different strategy, the small bank is more likely to be acquired by the large bank at a discount when the small bank fails and the large bank survives. In addition, the small bank would forego the likelihood of bailout subsidies in a crises triggered by the failure of the large bank.

Accordingly, herding is expected to be more prevalent in countries with an asymmetric banking sector. In an asymmetric banking sector, which is dominated by a few large banks, the market share difference between large banks and small banks is substantial. Hence, large banks in such a banking sector are likely too-big-to-fail, and the failure of one of these banks is likely to cause a severe impairment to the financial system (Nier *et al.*, 2007; Laeven, Ratnovski and Tong, 2016). More precisely, when one of these banks fails, the banking sector capacity to acquire failed banks is significantly reduced. This, in turn, increases liquidation costs, and regulators are more inclined to bailout banks. Therefore, small banks have more of an incentive to follow large banks in an asymmetric banking sector.

Several studies have suggested that herding is more likely to occur among symmetric agents. Bikhchandani and Sharma (2000) argue that groups are more likely to herd if they are sufficiently homogeneous, with each facing the same decision problem. However, in a symmetric banking sector, the lending decisions of banks are more likely a strategic substitute. This is because each bank has the same likelihood of acquiring the other when one of them fails (Perotti and Suarez, 2002). When a bank fails, the surviving bank can purchase the failing bank at a discount and increase its market share. Therefore, increasing the charter value of the surviving banks.

This study hypothesises that herding is positively related with the degree of asymmetry within the banking sector. In other words, banking sectors that are dominated by a few large banks are more prone to herding. The extent of asymmetry within a banking sector is measured by market concentration, which is defined as the size of the largest three banks in terms of total assets relative to the size of the total assets of the banking sector. Market concentration data for each county are collected from the World Bank Financial Structure Dataset as of June 2017. Considering the dataset only covers data until 2015, individual bank total assets data collected from Orbis Bank Focus are used to compute market concentration data for 2016.

In addition to the degree of size asymmetry, the ability of particularly large banks to differentiate themselves by taking different banking activities and diversifying their asset portfolio also affects herding. Acharya and Yorulmazer (2007) argue that large banks have a greater incentive to differentiate themselves. However, small banks are more inclined to herd. Nonetheless, when large banks differentiate themselves, herding may not necessarily prevail. This is because small banks, insisting on following large banks, are constrained by their capacity to diversify their portfolios, as large banks are endowed with more capital and better technology to access different markets. Furthermore, peer herding by small banks does not necessarily increases the likelihood of their bailouts when the aggregate size of these banks is not significant.

Accordingly, this study hypothesises that herding is positively related to restrictions on banking activities. Such restrictions limit the ability of large banks to differentiate themselves from others, therefore making it more feasible for small banks to mimic the activities of large banks. As proxies for the degree of activity restrictions in the banking sector, the activity restrictions index and the diversification index are both used. The former index measures the extent to which the regulator permits banks to engage in securities, insurance and real estate businesses. A higher value of the index indicates more restrictions. In addition, the latter index captures whether there are explicit guidelines for bank asset diversification and whether banks are permitted to provide offshore loans. Higher values of the index suggest more diversification. Data on both indexes are collected from Barth, Caprio and Levine (2013) based on World Bank surveys on bank regulation in 2011.

4. Regulatory and Supervisory Quality

Bailouts are more likely when the probability of banks turning weak is high or, in other words, in countries where supervisory quality and prudential regulation is weak. Brown and Dinç (2011) show that a government decision to liquidate a bank depends on the financial health of the overall banking system. Meanwhile, Acharya and Yorulmazer (2007) also argue that in the event an individual bank fails, the optimal decision for the government is to let the surviving banks acquire the failed bank. However, in multiple bank failures, it may be optimal to exhibit forbearance in the form of bailouts.

Moreover, according to Anginer, Demirguc-Kunt and Zhu (2014b), the adverse consequence of moral hazard due to deposit insurance can potentially be mitigated through better bank regulation and supervision. In particular, countries where the supervisory authorities have the power and authority to take preventive and corrective action, such as replacing the board of directors, are more likely to have more resilient banks.

Accordingly, this study hypothesises that herding is inversely related to the stringency of bank capital regulations and supervisory quality. Following Anginer, Demirguc-Kunt and Zhu (2014b), supervisory quality is measured by the official supervisory power index constructed by Barth, Caprio and Levine (2013) based on World Bank surveys on bank regulation in 2011. Supervisory power index indicates whether the supervisory authorities have the power and the authority to take specific preventive and corrective actions. A higher value of the index implies greater power.

In addition, according to Kara (2016), the effectiveness of the capital adequacy ratio is determined by how the regulator allows domestic banks to choose the numerator (equity capital) and the denominator (risk-weighted assets) of the ratio. Hence, the “overall capital stringency” index is used as a measure of the stringency of bank capital regulation instead of the minimum capital ratio requirement enforced within a country. Higher values of the index indicate greater stringency. The data for the former variable are collected from Barth, Caprio and Levine (2013) based on World Bank surveys on bank regulation in 2011.

2.4.4. Control Variables

To control for unobserved time variant country heterogeneity, several variables are used as measures of macroeconomic condition and systematic factors. These variables are likely to affect bank asset quality and bank performance and, hence, simultaneous response to common factors. Different herding measures are sensitive to different macroeconomic factors. Accordingly, the measures of macroeconomic condition and systemic factors used in the regressions depend on the herding measures.

With regards to the Z-Score LSV models, Uchida and Nakagawa (2007) use several variables to control for spurious herding: real GDP growth, the rate of increase in the index of land price, and the idiosyncratic impact of financial liberalisation in Japan in the 1980s as an institutional factor in herding. The index of land price is used to control for the increase in asset prices that contributes to lending booms. Following their approach, real GDP growth and inflation is included as control variables for the Z-Score LSV models. Real GDP growth and inflation rate are acquired from the International Monetary Fund World Economic Outlook 2018. In addition, because the DD LSV model is based on market data, annual stock market return is used instead as control variables for the model. Furthermore, following Bharath and Shumway (2008), annual stock return is calculated by cumulating daily returns over the year. Data on daily country stock market index are acquired from Datastream. Concerning the DGC models, similar to Billio *et al.* (2012), stock market return is used to control for common-factor exposure.

The extent of credit information availability may also affect the herding measures. Several studies on informational cascades in the banking literature (Chang *et al.*, 1997; Barron and Valev, 2000; Nakagawa and Uchida, 2011) have suggested that banks facing asymmetric information on their loans follow other banks perceived to have better access to private credit information, including credit information on new borrowers. Other studies (Rajan, 2006; Choi and Skiba, 2015), however, have suggested that the availability of public information may deter the search for private information, which in turn causes the financial market to become informationally less diversified and homogenous. In other words, financial institutions herd less when information asymmetry is high. To control for the effect of access to credit information on banks aggregate behaviour, a variable that measures the depth of publicly available credit information is included in the regressions.

Following several studies that have considered depth of credit information as a factor that determines bank stability (Beck, De Jonghe and Schepens, 2012; Anginer, Demirguc-Kunt and Zhu, 2014a), depth of credit information index from the World Bank Ease of Doing Business database is used as a measure of credit information depth. A higher value of the index indicates better access to credit information. The index is based on the assessment of a country's reporting system according to whether:

1. Both positive and negative information are available;
2. The information includes both firms and individuals;
3. Data from retailers and utility companies are provided, in addition to data from financial institutions;
4. The data cover more than a 2-year period;
5. Data on loans below 1% per capita are available; and
6. Laws guarantee borrowers the right to check their data in the largest registry in the country.

Moreover, DGC models and DD LSV model use listed banks as samples and Z-Score LSV models use both listed and non-listed banks. To control for differences in the sample characteristic of the herding measures, the ratio of the number of listed banks to total number of banks within a country is included in the Z-Score LSV model. The variable is computed using data on current bank listing status from Orbis Bank Focus. In addition, data are adjusted annually to account for the occurrence of banks delisted in a certain year based on the delisted date of the banks. Furthermore, to ensure consistency, the data are subsequently matched with those from Datastream.

2.4.5. Summary Statistics

Table 2.2 shows the summary statistics of the herding measures and country-specific variables used in this study. The explanatory variables are categorised into four main groups: shareholder protection laws; exposure to fiscal costs; banking sector characteristics; and regulatory and supervisory quality.

The *Z-Score LSV* measure and the DGC measures provide some initial support for the argument that banks herd to increase the likelihood of a collective bailout position should default occur. The positive value of these measures may indicate the possibility of correlated risk-taking from herding. Furthermore, as indicated by the interquartile range and standard deviation of the herding measures, the level of herding seem to be country dependent, indicating the relevance of country-specific characteristics, as theorised by Acharya and Yorulmazer (2007).

The other country level determinant variables in Table 2.2, as is expected for a cross-country study, indicate moderate levels of the shareholder protection laws, exposure to fiscal costs, banking sector characteristic and, regulatory and supervisory quality. However, the standard deviation suggests some cross-country variation in the determinants.

Table 2.3 shows that the pairwise correlations between the *Z-Score LSV* measure and both DGC measures, *DGC Two-Way* and *DGC One-Way*, are all positive and significant at the 10% level. This suggests that the *Z-Score LSV* measure and the DGC measures are correlated and consistent. However, the correlation between the *DD LSV* and *Z-Score LSV* measures is not statistically significant. In addition, *DD LSV* is negatively correlated with both DGC measures. This suggests that the *DD LSV* measure is less consistent with the other three measures.

A possible explanation for the results is that the LSV method requires a reliable threshold, P_t, to filter out spurious from active herding. In this study, the global trend in bank risk is used as the threshold because herding is measured at the country-level. However, the *DD LSV* measure only includes listed banks in the sample. The measure uses distance-to-default, which requires market data, as the underlying variable for the risk measure. Hence, to compute the global trend in bank risk for the *DD LSV* measure, the data of 575 listed banks from 53 countries are used. In contrast, the *Z-Score LSV* measure uses 6,889 listed and non-listed banks from 129 countries. As a further comparison, Uchida and Nakagawa (2007) use the entire population of a particular type of bank in Japan to detect herding among the respective type using the same LSV method.

In addition, the correlation between the *DGC Two-Way* and *DGC One-Way* measures is positive and stronger compared to the other measures. Nonetheless, according to the mean-comparison test presented in Table 2.4, the difference between both measures is statistically significant at the 1% level. This suggests that the *DGC One-Way* measure conveys additional information that may be useful to test whether the explanatory variables are consistent using different measures of herding.

Figure 2.1 presents the cross-country distribution of the degree of herding based on the value of Z_i^2 for the *Z-Score LSV*. A high Z_i^2 value may indicate herding within a country. Acording to the distribution of the Z_i^2 for the *Z-Score LSV*, Russia in 2014 is identified as an outlier in 2014 (22.03). A possible explanation for the high value is that in August 2014, the risks in the Russian banking sector increased significantly due to three factors: the imposition of international sanctions; a worsening economic outlook and the depreciation of the rouble (The Economist, 2014).

Even before the elevated risk in the aforementioned month, Russia's banking sector soundness had been worsening. In June 2014, banking profit declined by 14% year on year, with more than 25% banks recording a loss in that month compared with 18% a year earlier. Capital adequacy declined from 13.5% at the beginning of 2014 to 12.6% by the end of the third quarter. The share of non-performing loans also increased. In particular, overdue unsecured consumer debt increased by 2% between April and September 2014 to 11.3%.

In conclusion, the presence of the outlier suggests that the LSV method is subject to spurious herding. This finding is consistent with that of Uchida and Nakagawa (2007). Accordingly, they suggest controlling for spurious herding by adjusting the LSV measure using macroeconomic factors.

Figure 2.2 shows the country-level distribution of the yearly average *DGC Two-Way* and *DGC One-Way* measures. A higher value of DGC suggests a higher level of herding. The figure shows several extreme low values of DGC. Two countries are consistent as outliers across both measures: Spain and Austria. Concerning Spain, a possible explanation for the low DGC is that the sample only include listed banks, which are the six largest commercial banks in Spain, and does not include saving banks (cajas de ahorros), which were the main source of the financial crisis that occurred in the country. Furthermore, two of the banks in the sample (Santander and BBVA) hold a well-diversified asset portfolio in terms of geography, which enabled them to minimise the impact of the crisis occurring in Spain in 2008–2009. Many of the banks that failed during that period are small and specialised banks (Dewatripont, 2014; Maudos and Vives, 2016).

Regarding Austria, the country holds a universal banking system, allowing the banks to diversify their banking activities to include a wider range of products and services. According to Knobl (2018), there is no regulatory separation of Austrian banks into universal, commercial or retail banks. A universal bank would be a bank that has obtained licences to conduct activities in all relevant aspects of Article 1 of the Banking Act. The same applies for commercial and retail banks. Required licences can be "customised" to meet a bank's needs.

Furthermore, Austrian banks' activities are diversified geographically. According to IMF (2013), Austrian banks' subsidiaries have a significant market share in several Central, Eastern and Southeastern Europe countries and these market represent a significant share of the Austrian banking system total assets. The importance of these subsidiaries has increased over time in terms of both total assets and share of operating profit of the Austrian banking system. At the end of 2011, they represented 23.2% of total assets and 66% of net operating profit. Accordingly, the wide range of banking activities permitted may explain the reason for the low level of herding in Austria.

In conclusion, the ability of banks to diversify their asset portfolio and the wide range of banking activities permitted may explain the reason for the degree of low herding in the related countries. This is consistent with the hypothesis in this study that herding is positively related with restrictions on banking activities.

In addition to the low value outliers, Figure 2.2 shows large values of outliers in the *DGC Two-Way* measure. A significant contribution to the extreme value is the data for Nigeria in 2012. To reduce the effect of possibly spurious outliers, winsorising is considered for both DGC measures. Following several related cross-country studies

(Beck, De Jonghe and Schepens, 2012; Anginer, Demirguc-Kunt and Zhu, 2014a), both measures are winsorised at the 1st and 99th percentile levels.

2.5. Estimation Method

The relationship between herding and the aforementioned variables is represented by a panel-data model in the following functional form:

Herding = f(shareholder protection laws, exposure to fiscal costs, banking sector characteristics, regulatory and supervisory quality, control variables)

The above relationship could be linear or non-linear. Five testable models are proposed based on the methods to detect herding and the estimation methods used to examine the relationship between herding and its determinants, as presented in Table 2.5. These models can be categorised into two groups based on the methods used for testing herding: the LSV models and the DGC models.

The LSV probit models, *Z-Score LSV Probit* and *DD LSV Probit*, are binary response models in which the dependent variable in these models, the herding measure, has the value of one if according to the chi-squared test the null hypothesis of 'no herding' in equation (2.7) is rejected and zero otherwise. The functional form of the LSV probit models is as follows:

$$Pr\left(y_{i,t} \neq 0 \middle| \boldsymbol{x}_{i,t}\right) = g\left(\boldsymbol{x}_{i,t}, \boldsymbol{\beta}\right) \qquad (2.20)$$

Where $\boldsymbol{x}_{i,t}$ denotes the k dimensional vector of the explanatory variables for country i at time t and g(.) denotes the standard normal cumulative distribution function (probit), $\phi(\boldsymbol{x}'_{i,t}\beta)$.

Accordingly, the maximum likelihood estimation (MLE) is used to estimate the parameters for these models. The MLE estimator is the estimator that maximises the log-likelihood function of the non-linear joint density function of independent and identically distributed country-level observations, as follows:

$$\widehat{\boldsymbol{\beta}}_{MLE} = \arg\max_{\beta} \sum_{i=1}^{N} \sum_{t=1}^{T} \{\boldsymbol{y}_{i,t}\, log[g(\boldsymbol{x}_{i,t}, \boldsymbol{\beta})] + (1 - \boldsymbol{y}_{i,t})\, log[1 - g(\boldsymbol{x}_{i,t}, \boldsymbol{\beta})]\} \quad (2.21)$$

In the presence of heteroscedasticity, the pseudo-maximum likelihood estimator and a robust version of the covariance matrix estimator, the sandwich estimator, are used. The pseudo-maximum likelihood estimator is the estimator that maximises a function related to the log-likelihood function but is not equal to it due to heteroscedasticity. Nonetheless, the estimation result is robust to some degree of misspecification, conditional on the estimator being consistent (Wooldridge, 2002; Greene, 2017).

In addition to *Z-Score LSV Probit* and *DD LSV Probit*, the LSV models include *Z-Score LSV FE Logit*. The latter model is introduced as a comparison to the first model. More precisely, the *Z-Score LSV Probit* model may be exposed to the incidental parameters problem, as it uses maximum likelihood to estimate the parameters and country dummy variables to control for unobserved country-specific factors. The *Z-Score LSV FE Logit*, however, uses conditional (fixed effects) logistic regression as the estimation method. Therefore, the model is expected to generate consistent estimators in particular for the time-varying variables.

Concerning the DGC models, these models use the degree of Granger causality as the herding measure. The measure represents the fraction of herding relationship within a country based on the Granger causality test. Furthermore, according to the level of the restrictiveness of the herding test, the DGC models cover two different models: *DGC Two-Way* and *DGC One-Way*. The least-squares dummy-variables (LSDV) is used as the estimation method for these models with the following functional form:

$$y_{i,t} = \boldsymbol{x'}_{i,t}\boldsymbol{\beta} + \boldsymbol{x'}_{i}\boldsymbol{\delta} + \mu_i + \lambda_t + v_{i,t} \qquad (2.22)$$

Where $\boldsymbol{x}_{i,t}$ is a k dimensional vector of the time-variant determinants and for any *t*, $\boldsymbol{x}_{i,t}$ ~ *i.i.d.* across countries; $\boldsymbol{x}_i$ is a k dimensional vector of the time-invariant determinants; μ_i is the unobserved country-specific fixed effects; λ_t is the unobserved time effects and $v_{i,t}$ is the idiosyncratic component. For any *t*, *s*, $v_{i,t}$ is independent of $v_{j,s}$ when i ≠j.

Furthermore, any time-invariant variables in $\boldsymbol{x}_i$ may mimic the unobserved country-specific fixed effects variable μ_i which introduces perfect collinearity into the regression. To avoid the problem, the unobserved country-specific fixed effects variable for country observation in which perfect collinearity is presence is dropped. In addition, to address heteroscedasticity, the standard errors are adjusted for within correlation clustered at the country level.

2.6. Results

One of the objectives of this study is to test the hypothesis that country-level factors determine herding. These factors include shareholder protection laws, exposure to fiscal costs to cover a deposit insurance scheme, banking sector characteristics, and regulatory and supervisory quality.

Five testable models are presented in Table 2.6 based on the methods to detect herding and the estimation methods used to examine the relationship between herding and its determinants. Columns (1) and (2) presents the results from the DGC models

(*DGC Two-Way* and the *DGC One-Way*); columns (3) and (4) reports the results from the Z-Score models (*Z-Score LSV Probit* and *Z-Score LSV FE Logit)*; and column (5) provides the estimation based on the *DD LSV* measure. In addition, the estimation result using unwinsorised DGC measures is presented in Table 2.7 as a comparison to the result using winsorised DGC measures presented in Table 2.6.

As explained in section 2.4.2 of this chapter, the *DGC Two-Way* measure is computed using the linear Granger causality method (Billio *et al.*, 2012).The original purpose of the method is to measure the extent of connectedness between financial institutions. Hence, the measure derived from the method may also capture bank interconnectedness unrelated to herding. To further fit the linear Granger causality method within the context of herding, *DGC One-Way,* which excludes relationships with feedback effects, is proposed.

Table 2.6 shows that the results for the *DGC One-Way* model in column (2) and both Z-Score models (*Z-Score LSV Probit* and *Z-Score LSV Fixed Effects (FE) Logit*) in columns (3) and (4) are relatively consistent. Nonetheless, the results for the *DGC Two-Way* model in column (1) are less consistent with the other three measures. More precisely, in column (1), only *Market Concentration* significantly explains the cross-country variation of the *DGC Two-Way* measure. In contrast, other country-specific features such as: *Explicit DIS*, *Log Total Assets*, *International Debt*, *Activity Restrictions*, *Diversification Index, Capital Stringency* and *Supervisory Power Index*, also explain the variation of the other three herding measures in columns (2)–(4). This suggests that the restricted *DGC One-Way* method and the Z-Score LSV method both measure the same variable, herding, and that country-specific factors affect herding. However, the *DGC Two-Way* method is less effective in detecting herding.

The results for *Z-Score LSV FE Logit* in column (4) are consistent with that for *Z-Score LSV Probit* in column (3). In particular, the coefficients of the time-varying variables: *Log Total Assets*; *International Debt*; *Market Concentration*; *GDP Growth*; and *Inflation Rate* are all significant with consistent signs. However, the results from the *DD LSV Probit* model in column (5) are inconsistent compared to the other two LSV models. This is expected, considering that the dependent variable, *DD LSV* measure, may not have been properly constructed, as discussed in section 2.4.2 of this chapter.

The results in Table 2.6 suggest that several country-level factors significantly affect bank herding. In particular, exposure to fiscal costs, banking sector characteristics, and regulatory and supervisory quality. A country's exposure to fiscal costs is measured by both the presence of explicit deposit insurance (*Explicit DIS*) and the significance of the banking sector in the economy (*Log Total Assets* and *International Debt*). The coefficients of *Explicit DIS* in columns (2) and (3) are both positive and significant at the 1% level. This indicates that banks in countries with an explicit deposit insurance scheme are more inclined to herd. Furthermore, herding is more likely to occur when the banking sector in an economy is significant. This is indicated by the statistical significance and positive signs for *Log Total Assets* and the negative signs for *International Debt* in columns (2)–(4) respectively. The finding is consistent with the theory of Acharya and Yorulmazer (2007) that large fiscal costs lead to the too-many-to-fail phenomenon and ex-ante bank herding.

In addition, the results show that banking sector characteristics determine herding. The coefficients of *Market Concentration* are positive and significant at the 1% and 5% levels in columns (2)–(4). This suggests that countries with a concentrated or asymmetric banking sector are more vulnerable to herding. In a concentrated banking sector, the size difference between the largest and the smaller banks is large. Accordingly, the failure of one of the largest banks is likely to cause systemic risk, leading to government support (Nier *et al.*, 2007; Laeven, Ratnovski and Tong, 2016). The likelihood of bailouts provides an incentive for the smaller banks to herd (Acharya and Yorulmazer, 2007). When these banks choose to differentiate themselves and fail, the largest banks can acquire them at a discount. However, when the largest banks fail, these banks forego the likelihood of bailout subsidies in a crisis triggered by the failure of the largest banks.

The finding is also consistent with the strategic substitute hypothesis (Perotti and Suarez, 2002). In a symmetric banking sector, lending decisions of banks are more likely a strategic substitute. This is because each bank has the same likelihood of acquiring the other when one of them fails. When a bank fails, the surviving bank can purchase the failing bank at a discount and increase its market share. Hence, banks are more likely to herd in an asymmetric banking system compared to a symmetric one.

Moreover, the coefficients of *Activity Restrictions* in columns (2) and (3) are both positive and significant at the 5% and 1% levels respectively. In addition, those of *Diversification Index* are negative and significant at the 10% and 5% levels respectively. This suggests that activity restrictions induce herding. Although larger banks are more likely to pursue different strategies, regulations that restrict banking activities limit the ability of larger banks to differentiate themselves. This makes it more possible for smaller banks to herd.

Furthermore, the results show that herding is more likely to occur in countries where the banking sector regulatory and supervisory quality is weak. The coefficients of both *Capital Stringency* and *Supervisory Power Index* are all negative and significant in columns (2) and (3). This finding is consistent with Brown and Dinç (2011), who show that a government decision to liquidate a bank depends on the financial condition of the overall banking sector. These findings suggest that the occurrence of the too-many-to-fail phenomenon is less likely in countries that feature better regulatory and supervisory quality.

In addition, although most of the factors affect herding, the coefficients of *Investor Protection Laws* are statistically significant only for the LSV models in columns (3) and (4) at the 10% level. This suggests that shareholder protection laws may not explain the cross-country variation of herding. Therefore, the finding does not support the theory of Acharya and Yorulmazer (2007) that bank herding is more severe in economies with weaker shareholder protection laws. A possible explanation for why weak shareholder protection laws and, in turn, greater inside ownership of banks are less relevant in determining herding is that banks with dispersed ownership also enjoy bailouts subsidies. Hence, herding may occur in countries where shareholder protection laws are not necessarily weak.

More precisely, according to King (2009), during the global financial crisis in 2008 governments recapitalised the banks using a variety of instruments. Although the UK government uses a combination of common shares and preferred shares, most governments use hybrid securities such as preferred shares, subordinated debt or convertible debt to limit the risk of loss to taxpayer. Consequently, common shares are not entirely diluted. According to Goldman Sachs estimates (King, 2009), the recapitalisation program in UK led to a dilution of up to 60% but in US, it was only 9% in average.

In addition, Veronesi and Zingales (2010) estimate that the US government bailouts in 2008 increased the value of banks' financial claims by USD 130 billion at a taxpayers' cost of USD 21–44 billion. Furthermore, without the recapitalisation program, shareholders loss could have reached USD 25 billion, but instead they only lost USD 3 billion. This finding supports the argument that shareholders' ownership is less likely to be fully diluted in a crisis.

The results for the control variables show that the relationship between macroeconomic variables and herding is positive and significant at the 5% level for *GDP Growth* and the 1% level for *Inflation Rate* for both Z-Score LSV models in columns (3) and (4). This suggests that the measure also captures unintentional herding due to simultaneous response to changes in macroeconomic conditions (Uchida and Nakagawa, 2007). However, *Stock Return* as a proxy for systematic risk is not statistically significant in all the DGC models (columns 1 and 2). This finding supports Billio *et al.* (2012) and further suggests that contemporaneous common shocks do not explain herding based on the DGC measure. This indicates that the measure is robust to spurious herding.

In addition, compared to the DGC models both in columns (1) and (2), the number of observations in the LSV models in columns (3)–(4) are approximately half the size. This is because some of the country-level dummy variables in the LSV models, which are estimated using probit and logit regressions, generate perfectly predicted outcomes. Hence, the related observations are excluded to avoid biased and inconsistent estimates. Overall, the *Z-Score LSV Probit* in column (3) and *Z-Score LSV FE Logit* in column (4) each include 78 and 80 observations, both covering 26 countries. Although the number of sample is more limited, the results of both models are consistent with that of *DGC One-Way* in column (2), which uses 165 observations and includes 35 countries.

2.7. Robustness Checks

2.7.1. Alternative Measure of Shareholders' Protection Laws

To examine the sensitivity of the result with respect to the measure of the shareholder protection laws reported above, an alternative measure is considered. In particular, the protection of the minority shareholders' interest from the World Economic Forum Global Competitiveness Report is used to replace the *Investor Protection Index* as the variable for shareholder protection laws. The result, as presented in Table 2.8, is relatively consistent with the previous estimation in Table 2.6.

2.7.2. Testing for Simultaneity Bias

In addition to omitted variables, simultaneity is another source of endogeneity. Simultaneity exists when some of the right-hand side variables are jointly determined with the dependent variable. Several studies on competition and stability of banks have suggested that simultaneity may exist between competition and stability variables. Although this research is not directly related, the proposed models include market concentration as a proxy for the degree of size asymmetry within a banking sector and herding measures based on bank risk measures as the dependent variable. A common approach to address simultaneity bias is by using the instrumental variables (IV) estimation method.

Nonetheless, one of the disadvantage of using IV estimation is that the method is inefficient compared to OLS when the model is not exposed to simultaneity. According to Wooldridge (2016), TSLS estimators can have very large standard errors, which would lead to a less precise estimator and, therefore, misleading inference. Accordingly, a test is required to first determine whether reverse causality problem does exist in the regression.

Considering the presence of heteroscedasticity in the model, two-step generalised method of moments is used as the estimation method for the IV estimator, with a weight matrix adjusted for within correlation clustered at the country level. According to Baum, Schaffer and Stillman (2002), the GMM method provides a more efficient IV estimator in the presence of heteroscedasticity compared to TSLS. The same variables in the DGC One-Way model are used in the GMM-IV model, in addition to the IVs. Furthermore, to make the assumption of no correlation in the error term more likely to hold, the year dummy variable is included.

Before proceeding with the endogeneity test, the Hansen J test of overidentifying restrictions and Shea partial coefficient of determination are both used to choose the instruments that are valid and relevant from a pool of IVs that are selected with reference to related studies (Berger, Klapper and Turk-Ariss, 2009; Anginer, Demirguc-Kunt and Zhu, 2014a; Fu, Lin and Molyneux, 2014). The results of the tests are presented in Table 2.9.

The results confirm the appropriateness of the combination of financial freedom and the first lag of market concentration as IVs. Both instruments satisfy the validity conditions and the relevance conditions. The Hansen J-statistic, which is used to determine the validity of the overidentifying restrictions in a GMM model, does not reject the null hypothesis that $E[g(\boldsymbol{x}_{i,t}, y_{i,t}, \boldsymbol{z}_{i,t}, \boldsymbol{\beta})] = 0$ or that the instruments are valid. In this study, the moment function $g(\boldsymbol{x}_{i,t}, y_{i,t}, \boldsymbol{z}_{i,t}, \boldsymbol{\beta})$ is defined as $\boldsymbol{z}_{i,t}(y_{i,t} - \boldsymbol{x}'_{i,t}\,\boldsymbol{\beta})$, where $\boldsymbol{z}_{i,t}$ is a L x 1 vector of observable IVs. In addition, based on the F-statistic of the joint significance of the instruments in the first regression and the Shea's partial R-square, both instruments are significant and explain most of the variation of market concentration.

Furthermore, to test for simultaneity bias in the presence of heteroscedasticity, the difference-Sargan test or C statistic is used (Baum, Schaffer and Stillman, 2007). The test statistic is computed as the difference between two Sargan–Hansen J-statistics. The first is the J-statistic of the efficient regression, in which variables considered as endogenous are treated as exogenous. The second is that of the inefficient but consistent regression, in which IVs are used. In summary, the test statistics for the GMM–IV method is as follows:

$C = (J_e - J_c) \sim \chi^2_{(p)}$ under the null hypothesis that the specified variables are exogenous. (2.23)

Where p denotes the number of restrictions or the number of endogenous variables whose endogeneity is being tested; J_e and J_c each denotes the Sargan–Hansen J-Statistics for the efficient estimator and the inefficient but consistent estimator; and:

$$J_c = NT\bar{\mathbf{g}}\big(\boldsymbol{x}_{i,t}, y_{i,t}, \boldsymbol{z}_{i,t}, \widehat{\boldsymbol{\beta}}_{\boldsymbol{GMM}}\big)'\widehat{\boldsymbol{W}}\bar{\mathbf{g}}\big(\boldsymbol{x}_{i,t},, y_{i,t}, \boldsymbol{z}_{i,t,} \widehat{\boldsymbol{\beta}}_{\boldsymbol{GMM}}\big) \qquad (2.24)$$

Where $\bar{\mathbf{g}}\big(\boldsymbol{x}_{i,t}, y_{i,t}, \boldsymbol{z}_{i,t}, \widehat{\boldsymbol{\beta}}_{\boldsymbol{GMM}}\big) = \frac{\mathbf{1}}{\boldsymbol{NT}}\sum_{\boldsymbol{i=1}}^{\boldsymbol{N}}\sum_{t=1}^{T}\mathbf{g}(\boldsymbol{x}_{i,t}, y_{i,t}, \boldsymbol{z}_{i,t}, \widehat{\boldsymbol{\beta}}_{\boldsymbol{GMM}})$ and $\widehat{\boldsymbol{\beta}}_{\boldsymbol{GMM}}$ is the GMM estimator. $\widehat{\boldsymbol{W}}$ is the weight matrix of the moment conditions and is equal to the inverse of the moment covariance matrix.

Using commonly used IVs that satisfy the validity condition and the relevance condition, the null hypothesis that market concentration is exogenous is likely to be rejected. Nonetheless, the result of the C statistic as presented in Table 2.9 shows the opposite.

Moreover, using the same approach for the *DGC Two-Way* measure as the dependent variable, a similar result is obtained. In conclusion, the use of IVs does not significantly improve the consistency of the estimators, and there is no strong evidence to reject the hypothesis that market concentration is exogenous to the herding measures.

2.8. Conclusions

The objective of this chapter was to investigate whether banks do herd due to the likelihood of their bailouts and investigate the determinants of such herding. Herding measures were derived using the Granger causality test and the LSV method based on changes in Z-score and distance-to-default. In addition, following Billio *et al.* (2012), volatility-adjusted stock return was used for the Granger causality test. Further restriction was applied to fit the test within the herding context.

Next, the results of both methods were regressed on country-level factors considered as determinants of bank herding, with reference to the model of Acharya and Yorulmazer (2007): shareholder protection laws, exposure to fiscal costs, banking sector characteristics, and regulatory and supervisory quality, controlling for macroeconomic variables and depth of credit information. LSDV and maximum likelihood were used to estimate the parameters.

The empirical results show the possibility of bank herding and their behaviour is affected by several country-level factors, in particular: exposure to fiscal costs;

banking sector characteristics, and regulatory and supervisory quality. The finding is consistent with the theory of Acharya and Yorulmazer (2007).

However, although most of the country-specific factors are consistent with the theory, shareholder protection laws are not. A possible explanation for why weak shareholder protection laws and, in turn, greater inside ownership of banks is less relevant is that shareholders of banks with dispersed ownership also receive subsidies in the event their banks are bailed out. Accordingly, herding may occur in countries where shareholder protection laws are not necessarily weak. This supports the argument of Brown and Dinç (2011) that, given the evidence of regulatory forbearance amidst too-many-to-fail problems in emerging markets, similar cases are also possible in developed countries.

Several policy implications arise from the findings. First, the findings highlight the importance for regulators to set-up system-wide surveillance on banking risk. A system-wide perspective allows regulators to identify systemic-risk that may arise due to direct and/or indirect correlation among banks. Although from a micro perspective banks are individually reducing their risks, the likelihood of systemic risk may increase due to herding. Next, the findings highlight the importance of reducing exposure to the high fiscal costs that may arise from having an explicit deposit insurance scheme. This can be achieved, among other methods, by diversifying the source of financing in bank-centric economies through financial deepening initiatives.

Table 2.1
Sample coverage of the herding measures

This table shows the number of country-year observation used to compute each dependent variable. To be included in the sample, a country-year piece of data should consist of at least five banks. All dependent variables cover the same 5-year sample period (2012–2016). Furthermore, Z-Score LSV uses the largest data sets (314 country-year sample), covering 129 countries and 6,889 banks. However, DD LSV and DGC uses 245 and 241 country-year sample, each covering 53 and 51 countries and 575 and 615 banks. The data sets for both dependent variables only cover listed banks and hence, the sample size is not as large as that for Z-Score LSV. This is because market data are required to compute both measures. In addition, the difference in the sample size between DD LSV and DGC is due to the different components required to compute each measure. In particular, DD LSV uses distance-to-default as the risk measure for herding. However, DGC is based on volatility-adjusted stock return.

Measures	Data Level	# Obs.	Coverage			
			Period	Countries	# Banks on Average	Bank Status
Z-Score LSV	country	314	2012–2016 (5 years)	129	6,889 (U.S. banks: 5,597)	Listed and non-listed
DD LSV	country	245	2012–2016 (5 years)	53	575 (U.S. banks: 50)	Listed
DGC	country	241	2012–2016 (5 years)	51	615 (U.S. banks: 69)	Listed

Table 2.2
Summary statistics

This table shows the summary statistics for the herding measures and country-specific variables used in this study. The explanatory variables are categorised into four main groups. First, shareholders protection laws of a country are captured by the strength of the minority investor protection index. The second set of variables is related to exposure to fiscal costs, measured by the presence of an explicit deposit insurance scheme within a country, banking sector total assets (in thousands of USD) in natural logarithm and the ratio of non-financial corporation international debt to nominal GDP. Next, banking sector characteristics are captured by the market concentration, activity restrictions and diversification index. The last group of variables are related to regulatory and supervisory quality, which consists of the capital stringency and supervisory power index.

Variable	N	Q1	Mean	Median	Q3	Std. Dev
Herding Measures						
DGC Two-Way	241	9.058	13.571	12.088	16.667	8.617
DGC One-Way	241	6.667	10.129	10.000	13.187	5.648
Z-Score LSV	314	-0.058	0.023	0.003	0.086	0.109
DD LSV	245	-0.049	0.078	0.072	0.187	0.174
Shareholders Protection Laws						
Investor Protection Index	401	4.700	5.629	5.700	6.500	1.279
Exposure to Fiscal Costs						
Explicit DIS	401	1	0.756	1	1	0.430
Log Total Assets	402	10.359	11.915	11.879	13.382	2.161
International Debt (%)	297	0.985	7.992	4.153	9.396	14.544
Banking Sector Characteristics						
Market Concentration (%)	402	43.597	58.119	57.336	71.114	17.249
Activity Restrictions	342	6.000	7.178	7.000	9.000	2.036
Diversification Index	344	1.000	1.401	2.000	2.000	0.705
Regulatory and Supervisory Quality						
Capital Stringency	379	4.000	4.954	5.000	6.000	1.561
Supervisory Power Index	351	9.000	10.883	11.000	13.000	2.258
Control Variables						
GDP Growth (%)	398	1.605	2.994	2.981	4.687	2.821
Inflation Rate (%)	398	0.601	4.978	2.063	5.043	18.090
Stock Return (%)	306	-7.309	5.098	3.158	15.157	25.004
Credit Info Depth	401	5.000	5.142	5.000	7.000	2.156
Listed Banks (%)	402	15.789	46.504	44.444	77.778	33.140

Table 2.3
Pairwise correlation among the herding measures

This table provides information on the correlation between the herding measures. In parentheses and brackets below the correlation are the corresponding p-values and the number of observations, respectively. As correlations measure the linear relationship between two variables, linear forms of both Z-Score LSV and DD LSV are used instead of the binary response used in the LSV models. In particular, following Uchida and Nakagawa, $LSV_i = |P_i - P_t| - E|P_i - P_t|$, where P_i denotes the proportion of banks' risk measure that deteriorates in country-year i, P_t denotes the expected proportion of banks globally which risk increases in year t, and $E|P_i - P_t|$ is calculated based on the assumption that the distribution of a random value of $|P_i - P_t|$ follows a binomial distribution $E[|P_i - P_t|; X_i \sim (N_i, P_t)]$.

	Z-Score LSV	DD LSV	DGC Two-Way	DGC One-Way
Z-Score LSV	1.0000			
	[314]			
DD LSV	0.0844	1.0000		
	(0.2857)			
	[162]	[245]		
DGC Two-Way	0.1324	-0.1285	1.0000	
	(0.0994)	(0.0051)		
	[156]	[233]	[241]	
DGC One-Way	0.1510	-0.1241	0.6196	1.0000
	(0.0598)	(0.0585)	(0.0000)	
	[156]	[233]	[241]	[241]

Table 2.4

Paired t-test between DGC One-Way and DGC Two-Way

The mean-comparison test is used to compare two measures: DGC One-Way and DGC Two-Way, with the null hypothesis being that the mean difference between the two measures is zero at a significance level of 5%. The statistical significance (2-tailed p-value) of the paired t-test ($(\Pr(|T| > |t|)$ under Ha: mean (diff) $\neq 0$) is 0.000, suggesting both measures convey different information.

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
DGC One-Way	241	10.129	0.364	5.648	9.412	10.846
DGC Two-Way	241	13.571	0.555	8.617	12.477	14.664
Diff	241	-3.442	0.436	6.771	-4.301	-2.583

mean (diff) = mean(DGC One-Way – DGC Two-Way) t = -7.892

Ho: mean (diff) = 0 df = 240

Ha: mean (diff) < 0	Ha: mean (diff) ≠ 0	Ha: mean (diff) > 0
Pr(T < t) = 0.000	Pr(T > t) = 0.000	Pr(T > t) = 1.000

Table 2.5
Summary of the models and related variables

Panel A. below presents the list of the five testable models in this study. LSV is used to test the null hypothesis of no herding within a country-year observation, based on the co-movement of the risk measures (ΔZ-score and Δdistance-to-default) of banks. A significance level of 5% is used to reject the hypothesis. The test result, whether the null hypothesis is rejected or not, generates the binary dependent variable for Model #1 and Model #3 in Panel A (Z-Score LSV) and Model #2 in Panel A (DD LSV). Although both models use the same risk measure (ΔZ-score), Model #1 and Model #3 in Panel A are different in their estimation methods. Model #4 in Panel A (DGC One-Way) uses the same method as that of Billio et al. (2012). In particular, the model uses the Granger causality test to test whether a bank is connected with other banks, with volatility-adjusted return as the underlying variable. To fit the test within the herding context, Model #5 in Panel A (DGC Two-Way), which uses further restricion, is introduced. Instead of a two-way, a one-way Granger causality is employed, thereby excluding relationships with feedback effects. These dependent variables are subsequently regressed on bank herding determinants in Panel B.

Dependent Variable		Explanatory and Control Variables	Estimation Methods
Risk Measure	Method for Testing Herding Hypothesis		
ΔZ-score	LSV	1.1 - 1.7., 2.1., 2.2., 2.4.-2.7.	Probit regression
ΔDistance-to-default	LSV	1.1 - 1.7, 2.3.-2.7.	Probit regression
ΔZ-score	LSV	1.1, 1.3. - 1.5., 2.1., 2.2., 2.4.-2.6.	Conditional (fixed effects) logistic regression
Volatility-adjusted stock return	Two-way Granger causality	1.1 - 1.7, 2.3.- 2.7.	Least-squares dummy-variables
Volatility-adjusted stock return	One-way Granger causality	1.1 - 1.7., 2.3.- 2.7.	Least-squares dummy-variables

Table 2.5 (*continued*)
Summary of the models and related variables

Panel B. below presents the list of explanatory and control variables in the models.

Shareholder protection laws
1.1. Strength of a country's shareholder protection laws
Exposure to fiscal costs
1.2. The existence of an explicit deposit insurance scheme within a country
1.3. The natural logarithm of the size of the banking sector total assets in thousands of USD
1.4. The size of non-financial corporation international debt securities outstanding to nominal GDP
Banking sector characteristics
1.5. The size of the largest three banks in terms of total assets relative to the size of the banking sector total assets
1.6. Activity restrictions index and diversification index
Regulatory and supervisory quality
1.7. Overall capital stringency index and supervisory authorities' power and authority to take preventive and corrective actions
Control Variables
2.1. Real GDP growth
2.2. Inflation rate
2.3. Stock market return
2.4. Depth of credit information
2.5. Ratio of the number of listed banks to total number of banks
2.6. Year dummy variables
2.7. Country dummy variables

Table 2.6
Bank herding and country-specific factors relationship

This table reports coefficient estimates on the relationship between bank herding and country-specific factors. The standard errors, reported in parentheses below the coefficient estimates, are adjusted for within correlation clustered at the country level. *, ** and *** indicate significance 10, 5 and 1 percent respectively. DGC Two-Way and DGC One-Way both use the least-squares dummy-variable as the estimation method and the fraction of herding relationship within a country based on Granger causality test as the dependent variable. DGC One-Way excludes a feedback mechanism. For Z-Score LSV Probit and DD LSV Probit, both models use probit regression as the estimation method with a binary dependent variable based on the result of whether the null hypotesis of no herding is rejected using the LSV method. Z-Score LSV FE Logit is introduced as a comparison to Z-Score LSV Probit, as the latter may be exposed to the incidental parameters problem. Country fixed effects and year fixed effects are included to control for time-invariant country heterogeneity and unobserved time effects, respectively.

	(1)	(2)	(3)	(4)	(5)
	DGC Two-Way	DGC One-Way	Z-Score LSV Probit	Z-Score LSV FE Logit	DD LSV Probit
Shareholder Protection Laws					
Investor Protection Index	0.505	0.975	-2.218*	-2.461*	-0.347
	(1.195)	(0.982)	(1.234)	(1.258)	(0.252)
Exposure to Fiscal Costs					
Explicit DIS	28.335	33.292***	103.292***		-39.970***
	(24.124)	(12.162)	(34.829)		(13.761)
Log Total Assets	2.417	3.541**	12.966***	12.982***	-5.063***
	(2.963)	(1.498)	(4.452)	(4.270)	(1.561)
International Debt	-0.882	-0.857**	-1.497**	-1.481*	-0.302**
	(0.533)	(0.399)	(0.695)	(0.817)	(0.124)
Banking Sector Characteristics					
Market Concentration	0.242***	0.137***	0.227**	0.241**	-0.082
	(0.051)	(0.036)	(0.110)	(0.113)	(0.051)
Activity Restrictions	1.595	4.775**	12.293***		4.459***
	(3.466)	(1.875)	(4.692)		(1.377)
Diversification Index	-12.374	-22.041*	-52.909**		-42.382***
	(19.926)	(10.940)	(22.721)		(15.876)
Regulatory and Supervisory Quality					
Capital Stringency	-12.309	-15.751***	-34.861***		-22.436***
	(8.682)	(5.315)	(12.372)		(7.665)
Supervisory Power Index	-7.967	-11.908**	-33.438***		14.068***
	(9.855)	(4.998)	(12.502)		(4.618)
Control Variables					
GDP Growth			0.499**	0.491**	
			(0.210)	(0.223)	
Inflation Rate			0.135***	0.132***	
			(0.038)	(0.040)	
Stock Return	0.020	0.015			-0.001
	(0.028)	(0.015)			(0.012)
Credit Info Depth	-0.759	1.273	-0.563	-0.541	0.142
	(1.482)	(0.874)	(0.447)	(0.455)	(0.254)
Listed Banks			-0.008	-0.006	
			(0.034)	(0.040)	
Number of countries	35	35	26	26	28
Number of observations	165	165	78	80	136
R-squared	0.491	0.544			
Pseudo R-Squared			0.412	0.421	0.217
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes

Table 2.7
Unwinsorised DGC measures

The table reports coefficient estimates on the relationship between bank herding and country-specific factors. Different to the result presented in Table 2.6, the estimation result in this table uses unwinsorised DGC measures. Furthermore, similar to the result in Table 2.6, the standard errors reported in parentheses below the coefficient estimates are adjusted for within correlation clustered at the country level and. *, ** and *** indicate significance 10, 5 and 1 percent respectively. Country fixed effects and year fixed effects are used to control for time-invariant unobserved country heterogeneity and unobserved time effects respectively.

	(1) DGC Two-Way	(2) DGC One-Way	(3) Z-Score LSV Probit	(4) Z-Score LSV FE Logit	(5) DD LSV Probit
Shareholder Protection Laws					
Investor Protection Index	0.410	1.091	-2.218*	-2.461*	-0.347
	(1.225)	(1.035)	(1.234)	(1.258)	(0.252)
Exposure to Fiscal Costs					
Explicit DIS	13.543	35.376***	103.292***		-39.970***
	(36.085)	(12.495)	(34.829)		(13.761)
Log Total Assets	0.827	3.640**	12.966***	12.982***	-5.063***
	(4.248)	(1.507)	(4.452)	(4.270)	(1.561)
International Debt	-0.795	-1.001**	-1.497**	-1.481*	-0.302**
	(0.564)	(0.456)	(0.695)	(0.817)	(0.124)
Banking Sector Characteristics					
Market Concentration	0.238***	0.142***	0.227**	0.241**	-0.082
	(0.051)	(0.038)	(0.110)	(0.113)	(0.051)
Activity Restrictions	-0.647	5.060**	12.293***		4.459***
	(5.293)	(1.921)	(4.692)		(1.377)
Diversification Index	-0.597	-22.298*	-52.909**		-42.382***
	(29.159)	(11.042)	(22.721)		(15.876)
Regulatory and Supervisory Quality					
Capital Stringency	-7.351	-17.176***	-34.861***		-22.436***
	(12.463)	(5.692)	(12.372)		(7.665)
Supervisory Power Index	-1.956	-12.151**	-33.438***		14.068***
	(14.705)	(5.026)	(12.502)		(4.618)
Control Variables					
GDP Growth			0.499**	0.491**	
			(0.210)	(0.223)	
Inflation Rate			0.135***	0.132***	
			(0.038)	(0.040)	
Stock Return	0.023	0.016			-0.001
	(0.029)	(0.015)			(0.012)
Credit Info Depth	-1.993	1.339	-0.563	-0.541	0.142
	(2.559)	(0.881)	(0.447)	(0.455)	(0.254)
Listed Banks			-0.008	-0.006	
			(0.034)	(0.040)	
Number of countries	35	35	26	26	28
Number of observations	165	165	78	80	136
R-squared	0.482	0.555			
Pseudo R-Squared			0.412	0.421	0.217
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes

Table 2.8

Alternative measure of shareholder protection laws

The table presents coefficient estimates of robustness tests using the protection of minority shareholders' index from the World Economic Forum Global Competitiveness Report as a proxy of the strength of shareholder protection laws (replacing the Investor Protection Index from the World Bank Ease of Doing Business annual database in Table 2.6). Data on protection of minority shareholders' interest are obtained from the World Economic Forum Global Competitiveness Report. The standard errors, reported in parentheses below the coefficient estimates, are adjusted for within correlation clustered at the country level. *, ** and *** indicate significance 10, 5 and 1 percent respectively.

	(1)	(2)	(3)	(4)	(5)
	DGC Two-Way	DGC One-Way	Z-Score LSV Probit	Z-Score LSV FE Logit	DD LSV Probit
Shareholder Protection Laws					
Minority Shareholder Protection	-3.836	-3.290	0.386	0.410	2.027*
	(3.735)	(2.747)	(1.749)	(1.569)	(1.138)
Exposure to Fiscal Costs					
Explicit DIS	19.367	25.381*	78.968**		-34.207**
	(24.479)	(12.972)	(30.738)		(14.452)
Log Total Assets	2.483	3.542**	10.283**	10.245**	-4.999***
	(2.830)	(1.468)	(4.056)	(4.124)	(1.624)
International Debt	-0.908	-0.901**	-1.568**	-1.577*	-0.270**
	(0.550)	(0.437)	(0.736)	(0.957)	(0.116)
Banking Sector Characteristics					
Market Concentration	0.231***	0.129***	0.152**	0.160*	-0.079*
	(0.052)	(0.044)	(0.074)	(0.091)	(0.044)
Activity Restrictions	1.371	4.489**	9.237**		3.564***
	(3.391)	(1.781)	(4.173)		(1.361)
Diversification Index	-3.859	-12.398	-43.874*		-38.289**
	(19.858)	(10.680)	(22.951)		(16.465)
Regulatory and Supervisory Quality					
Capital Stringency	-9.958	-12.831**	-32.561**		-19.671**
	(8.180)	(4.820)	(12.874)		(7.790)
Supervisory Power Index	-4.917	-8.774*	-25.083**		12.186***
	(9.814)	(4.995)	(11.308)		(4.703)
Control Variables					
GDP Growth			0.431**	0.423*	
			(0.212)	(0.227)	
Inflation Rate			0.123***	0.119***	
			(0.040)	(0.044)	
Stock Return	0.019	0.015			-0.002
	(0.027)	(0.017)			(0.011)
Credit Info Depth	-0.592	1.426	-0.637	-0.640	0.018
	(1.532)	(0.847)	(0.442)	(0.476)	(0.285)
Listed Banks			-0.011	-0.008	
			(0.034)	(0.040)	
Number of countries	35	35	26	26	28
Number of observations	165	165	78	80	136
R-squared	0.495	0.544			
Pseudo R-Squared			0.400	0.406	0.235
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes

Table 2.9
Testing for simultaneity bias

The table shows the result of using a series of test to identify whether the instrumental variables (financial freedom and first lag of market concentration) satisfy the validity condition and relevance condition and whether market concentration is endogenous to the herding (DGC One-Way) measure. The test of overidentifying restrictions is based on an efficient GMM estimator and uses the Hansen J test statistic to test the null hypothesis that the overidentifying restrictions are valid or $E[g(\mathbf{x}_i, y_i, \mathbf{z}_i, \boldsymbol{\beta})] = 0$. The partial R-sq from the first-stage regression summary statistics and Shea's partial R-square measures the correlation between the instrumental variables and the market concentration or relevance conditions. The GMM C test measures the difference between two Sargan-Hansen J-Statistics. The first is the J-statistic of the efficient regression, where market concentration is treated as exogenous. The second is the inefficient but consistent regression, where instrumental variables are used and market concentration is treated as endogenous. The null hypothesis that market concentration is exogenous is rejected when the difference is statistically significant.

Test of overidentifying restriction

Hansen's J chi2(1) = .409608 (p = 0.5222)

First-stage regression summary statistics

Variable	R-sq.	Adj. R-sq.	Partial R-sq.	Robust F (2,147)	Prob > F
Market Concentration	0.8307	0.8091	0.7661	322.4590	0.0000

Shea's partial R-square

Variable	Shea's Partial R-Sq	Shea's Adj. R-sq
Market Concentration	0.7661	0.7318

GMM C test

Ho: variables are exogenous

GMM C statistic chi2(1) = .85691 (p = 0.3546)

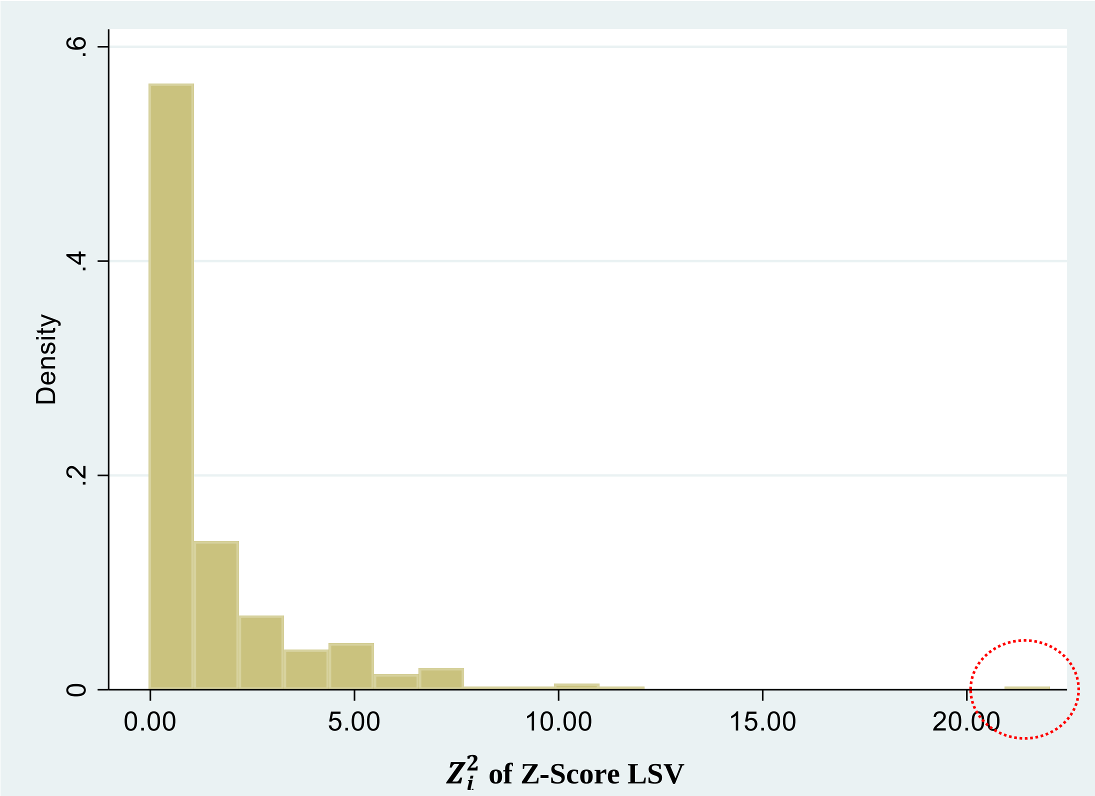

Figure 2.1 Country-year distribution of the Z_i^2 for Z-Score LSV. The figure displays the country-year distribution of Z_i^2 for Z-Score LSV, where $Z_i^2 \equiv \frac{(P_i - P_t)^2}{P_t(1 - P_t)/N_i}$. A high Z_i^2 value may indicate herding within a country. Nonetheless, a chi-square test is required as an additional step to filter-out Z_i^2 values that are not statistically significant. This is necessary to reduce the probability of type 1 error of having to suggest a high Z_i^2 value as herding within a country when it is not. Based on the histogram chart, the Z_i^2 for Russia in 2014 (22.03), marked by a red dot circle line, is well above the others. The high value may reflect common exposures to adverse macroeconomic and financial market conditions. This necessitates the inclusion of macroeconomic factors in the LSV models to control for spurious herding.

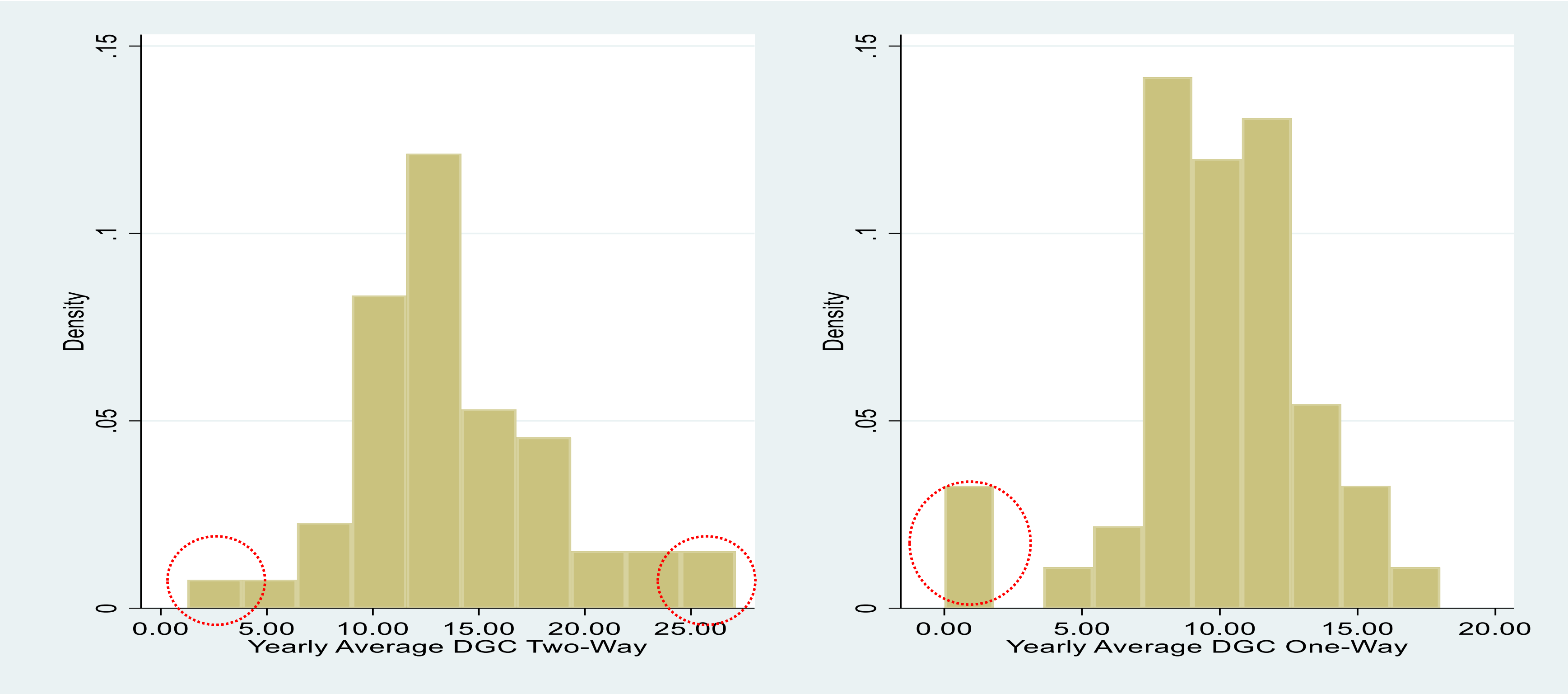

Figure 2.2 Country-level distribution for DGC measures. The figure displays the country-level distribution of the yearly average DGC Two-Way and DGC One-Way measure. Several low values of DGC outliers are identified. Two countries are consistent as outliers in both measures: Spain and Austria. The asset diversification and the wide range of banking activities permitted may have contributed to the low degree of herding in both countries. The DGC Two-Way measure also exhibits large value of outliers. The extreme value is mainly due to data for Nigeria in 2012.

3. Systemic Risk Implications of Bank Herding

3.1. Introduction

In a joint study by the International Monetary Fund (IMF), the Bank for International Settlements (BIS) and the Financial Stability Board (FSB) (2009), "systemic risk" is defined as a risk that causes significant financial stability impairment. According to BIS (2010), systemic risk covers time-series and cross-sectional aspects. The source of instability across time is known as "procyclicality", which arises from market participants' behaviour in response to the business cycle. In addition, the cross-sectional aspect is related to direct and indirect spillover effects amplifying negative shocks in time of crises due to institutions interconnectedness. Theoretical work on systemic risk has shown that bank interconnectedness can increase this risk through different propagation channels (Chen, 1999; Allen and Gale, 2000). Hence, it can be inferred that smaller banks can increase systemic risk when they are connected.

Existing studies in the banking literature, however, have focused more on the systemic risk of too-big-to-fail banks (Shleifer and Vishny, 2010; Laeven, Ratnovski and Tong, 2016) and individual bank vulnerabilities as determinants of systemic risk (López-Espinosa *et al.*, 2012; Adrian and Brunnermeier, 2016). Only a limited number of studies have focused on the problem of systemic risk as a herd, in which banks are not individually systemically important but take similar risks.

Lesser attention on the systemic risk nature of smaller banks is also reflected in the current regulatory framework, which emphasises more the systemic risk of too-big-to-fail institutions. More precisely, Basel III regulations impose several requirements to address systemic risk. Concerning the time-series dimension of systemic risk, the regulatory framework introduces a countercyclical capital buffer to mitigate procyclicality. As for cross-sectional dimension, designated systemically important banks are required to hold additional capital buffer against risk weighted assets.

Benoit *et al.* (2017) argue that Basel III does not explicitly discourage bank herding and may actually increase systemic risk by inducing commonality across banks. A stress test, for example, requires banks to have adequate capital to absorb the same shocks, discouraging banks from taking the opposite view. Horváth and Wagner (2017) also warn that the implementation of a countercyclical capital requirement creates an incentive for banks to invest in correlated activities.[12] To address procyclicality, they suggest focusing instead on policies that mitigate correlation among banks.

Understanding how herding contributes to systemic risk can help regulators detect the build-up of risk in the banking sector. This chapter examines the impact of bank herding on systematic risk by connecting it to individual bank vulnerabilities, consistent with the view that bank herding can reinforce the propagation channels of systemic risk (Acharya and Yorulmazer, 2007; Farhi and Tirole, 2012; Benoit *et al.*, 2017). Although there are several empirical studies on bank herding (Jain and Gupta, 1987; Barron and Valev, 2000; Uchida and Nakagawa, 2007), these have had more of an emphasis on methods to detect herding and have not measured the effect of herding on systemic risk.

[12] Horváth and Wagner (2017) argue that countercyclical capital buffer is expected to limit volatility returns from banks common exposure. Hence, banks are more inclined to lend to similar industries to smooth their earnings.

Systemic risk prevention is important considering the high cost of ex-post government support during financial crises. The cost of bank bailouts in the 1997 Asian Financial Crises is estimated at around 20–50% GDP for Thailand, Indonesia, South Korea and Japan (Calomiris, 1999). In addition, the bailout cost due to the 2008 Global Financial Crisis in the U.S. and Euro Areas was approximately 4.5% and 3.9% of GDP, respectively (Dewatripont, 2014). Accordingly, further empirical research is necessary to examine whether bank herding poses a systemic risk and to identify room for regulatory improvements to mitigate the risk.

This study contributes to the discussion on herding and systemic risk by providing an empirical assessment on the systemic risk implications of herding. The empirical result shows that herding amplifies the effect of individual bank vulnerabilities on systemic risk. More precisely, the interactions between individual bank vulnerabilities and herding are statistically significant in explaining systemic risk variation across banks. The finding highlights the importance of accounting for bank interconnectedness in systemic risk analyses.

In addition, this study suggests that the market may have expectations of bailout subsidies should banks collectively default. This is indicated by the lower estimated capital shortfall under a severe systematic shock, SRISK, for banks that herd. The findings are consistent with the theory that the likelihood of government bailouts induces herding (Acharya and Yorulmazer, 2007; Farhi and Tirole, 2012).

This chapter argues that there is potential for regulatory improvements, despite several regulations introduced to address systemic risk. The empirical result shows that the interaction between herding and bank funding structure and that between herding and bank assets structure are both statistically significant. This suggests that negative externalities from excessive funding risk and liquidity risk taking may not have been fully internalised through existing regulations. Accordingly, requirements on liquidity standards can be linked with the cross-sectional dimension of systemic risk to mitigate the impact of herding on systemic risk.

Both Laeven, Ratnovski and Tong (2016) and Cai *et al.* (2018) relate the source of systemic risk to different measures of systemic risk. Nonetheless, this is different from the work of Laeven, Ratnovski and Tong (2016), as the latter focus on bank size as the determinant of systemic risk and uses large institutions as their sample. In addition, Cai *et al.* (2018) study systemic risk that arises from bank interconnectedness in a syndicated loan portfolio. The current study is different from theirs as their findings are related to the interconnectedness that arises due to negative externalities from a diversification strategy (Wagner, 2010; Ibragimov, Jaffee and Walden, 2011). However, this study focuses on increased interconnectedness as a consequence of banks actively engaging in systemic risk taking through herding (Acharya and Yorulmazer, 2007; Farhi and Tirole, 2012).

3.2. Research Objective

The key objective of this research is to provide an empirical assessment on the effect of herding on systemic risk. An empirical assessment is required to provide some insights on the systemic risk implications of herding. Knowing how herding contributes to systemic risk helps regulators to detect and prevent the build-up of risk in the banking sector.

3.3. Literature Review

3.3.1. What is Systemic Risk?

The IMF, BIS and FSB (2009) define systemic risk as a risk that cause significant financial stability impairment. Furthermore, systemic risk encompasses two dimensions, time-series and cross-sectional (BIS, 2010). The discussion in this chapter emphasises more the cross-sectional dimension of systemic risk. This is consistent with the definition of herding in this research. In particular, herding is defined as the mechanism by which banks increase their correlation and the likelihood of a collective bailout position should default occur.

Furthermore, systemic risk can be triggered by different systemic shocks. De Bandt and Hartmann (2000) propose two types of shocks: idiosyncratic and systematic. The former are those which emanate from the distress of an individual bank, whereas the latter are shocks that affect multiple banks simultaneously. Furthermore, they argue that the identification of the different types of systemic shocks has important implications for crisis management policies. In particular, the spillover of bank failure due to the contagion effect could be prevented with emergency liquidity assistance. However, systematic shocks are commonly addressed using stabilisation policies such as open market operations. The channels via which the distress of an individual bank is transmitted to a large part of the banking system are explained further in the next section.

3.3.2. Propagation Channels

Several studies have proposed different propagation channels of systemic risk, which explain how a small or idiosyncratic shock can lead to a system-wide failure in the banking system. For example, Allen and Carletti (2013) define systemic risk by categorising the risk into four types: (a) panics, which is a banking crisis due to coordination failure; (b) banking crises due to asset price falls; (c) contagion from direct linkages and asset commonality; and (d) foreign exchange mismatches in the banking system. Furthermore, Freixas and Rochet (2008) suggest that systemic crises may develop either as a result of macroeconomic shock and contagion. The latter may occur through four nonexclusive channels: (a) shift in market expectations; (b) large-value payments systems; (c) over-the-counter operations; and (d) direct linkages in the interbank markets. Moreover, Cai *et al.* (2018) propose three channels of contagion among financial institutions: (a) direct exposure among financial institutions; (b) information-based contagion; and (c) assets commonality.

De Bandt and Hartmann (2000) differentiate two main channels through which financial contagion materialises in the banking system: (a) the exposure channel and (b) the informational channel. The former is related to financial contagion from direct interbank balance-sheet exposures, which may arise from interbank money market and/or payment system transactions. The latter is related to contagious withdrawals when depositors have imperfect information on the type of shocks hitting the bank and the extent of direct exposure among the banks.

Consistent with the focus of this research, further discussion on the propagation channels emphasises more those that are related to the cross-sectional dimension of systemic risk. In particular, this chapter focuses on two broad channels: (a) balance-sheet channel and (b) information channel. The former covers contagion from direct linkages and asset commonality. The latter encompasses contagion that arises from depositors' behaviour.

1. Balance-Sheet Channel

Hypotheses related to the balance-sheet channel explain how banks' balance-sheet exposures can lead to systemic risk. In particular, systemic risk may arise from direct exposures among banks, i.e. counterparty risk, and indirect exposures, i.e. common asset exposures and fire-sale externalities.

Concerning counterparty risk, Allen and Gale (2000) propose a model to explain contagion that emanates from financial claims among banks in the money market. Banks engage in interbank lending and borrowing to provide insurance against idiosyncratic liquidity shocks, which are imperfectly correlated. Nonetheless, the system is financially vulnerable. The impact of an aggregate liquidity shock experienced by a participant bank may spillover throughout the interbank market, conditional on the network structure of the market. Dasgupta (2004) arrives at a similar conclusion, using local shocks to bank assets instead of liabilities as the source of bank failure that leads to bank run.

However, Ahnert and Georg (2017) argue that direct linkages among banks do not necessary lead to systemic risk. The reason is that the potential of information spillover arising from counterparty risk reduces the likelihood of collective failure. Banks, responding to information contagion, implement conservative ex-ante measures by lowering counterparty risk and hoarding liquidity.

Several studies have generated similar results to the theory of Ahnert and Georg (2017). In particular, Furfine (2003), estimating bilateral exposure from the federal fund market, finds little evidence of contagion following simulated idiosyncratic defaults. In addition, Elsinger, Lehar and Summer (2006), studying bilateral inter-bank exposures in the Austrian banking system, find that correlation of bank asset portfolios contributes more to systemic risk than contagion from direct interconnectedness.

Concerning common asset exposures, Ibragimov, Jaffee and Walden (2011) argue that common assets in banks' diversified trading portfolio present another channel of systemic risk. If all banks hold the same diversified portfolio, a common shock may cause financial distress for all of these banks simultaneously. Similarly, Lehar (2005) suggests that the probability of systemic risk is related to joint dynamics of asset portfolios among banks.

In addition, Allen, Babus and Carletti (2012) suggest that the problem of systemic risk from asset commonality arises when assets are funded using short-term debt. More precisely, although banks asset portfolios are individually well diversified, they may overlap with one another because the number of available assets is limited. Therefore, banks asset structure can be divided into two different groups. First, an un-concentrated structure in which banks own different assets and where failures are more dispersed. Second, a concentrated structure, in which a cluster of banks invest in similar assets, therefore making joint default more likely. Furthermore, when banks assets are financed with short-term debt, the latter structure is more fragile to negative shock. More precisely, in the presence of adverse information on other banks, bank creditors may choose to terminate their short-term loan to their bank because of concerns that their bank would also default. Hence, the clustered structure is more prone to systemic risk when assets are funded using short-term borrowing.

The role of a bank's liability structure in increasing systemic risk from asset commonality is also emphasised by Agur (2014). He argues that lower portfolio correlation among banks does not necessarily lead to a more stable funding market for banks. Instead, funding vulnerability transmitted via the wholesale market can be mitigated when banks have a higher portion of retail deposits. Tasca, Mavrodiev and Schweitzer (2014) also propose a model in which financial institutions including banks implement different strategies, in particular strategies on leverage and asset diversification. According to their model, diversification strategy plays an important role in mitigating losses from investments. Nonetheless, leverage strategy, which enables a bank to increase their expected equity return by tilting their debt-to-equity composition, may amplify the default risk of the bank.

Concerning fire-sales externalities, Cifuentes, Ferrucci and Shin (2005) point out that forced sales of illiquid assets by a distressed financial institution can destabilise the market and lead to a contagious effect. In particular, the price effect of the forced sales may induce further sales, as it interacts with capital requirements and risk management policy of other banks, causing a downward spiral in asset prices.

In addition, due to their systemic importance, large banks are considered a source of contagion and systemic risk. Several studies have supported the view that large and complex banks contribute to this risk. Laeven, Ratnovski and Tong (2016) classify the related studies into three categories. First, the unstable banking hypothesis, which argues large banks tend to engage more in risky activities and use short-term debt (Shleifer and Vishny, 2010; Boot and Ratnovski, 2016). Second, the too-big-to-fail hypothesis, which suggests that large banks take excessive risks due to government bailout expectations (Black and Hazelwood, 2013; Duchin and Sosyura, 2014). Third, the agency cost hypothesis, which points out that large and complex banks engaging in multiple activities suffer from increased agency problems and poor corporate governance that can pose systemic risk (Laeven and Levine, 2007).

2. *Information Channel*

The information channel may cause contagious withdrawals due to depositors' rational responses under incomplete information and negative payoff externality. The latter arises due to sequential service constraint inherent in demand deposits (Chen, 1999). The hypothesis on contagion through the information channel is related to the classical hypothesis on the bank run, in which the former hypothesis is an extension of the latter to multiple banks system (De Bandt and Hartmann, 2000). Hence, to ensure a comprehensive view on contagion from the information channel, the literature on bank runs is elaborated in the following discussion.

Two strands of literature provide hypotheses on bank runs and their extension to multiple banks: (a) Pure-panic bank runs and (b) Information-based bank runs. Both hypotheses are based on different assumptions regarding the extent of the asymmetric information problem inherent in the banking system. In particular, the former hypothesis assumes depositors are uniformed about the true state of their bank. Hence, pure-panic bank runs are random phenomena which lead to a self-fulfilling prophecy. The latter relaxes the assumption, suggesting depositors have private but imperfect information on bank assets quality. Hence, information-based bank runs may also lead to social inefficiency when they do not reflect bank fundamentals.

One of the seminal studies on pure-panic bank runs is Diamond and Dybvig (1983). They assume that the consumption needs of depositors are uncertain and the sell of long-term investments generates costs. Depositors place their funds in a bank because banks provide a liquidity guarantee on depositors' idiosyncratic consumption needs. To meet the insurance claim, the bank holds a fraction of the deposits in reserve.

Therefore, as long as deposit withdrawal remains idiosyncratic, the bank does not need to sell their long-term investments.

Nonetheless, due to asymmetric information, depositors are uncertain regarding the fundamentals of their bank and the actions of other depositors. This reduces the ability of depositors to precisely coordinate their arbitrary actions and beliefs. Therefore, a bank run can occur when depositors are not confident with their bank and believe other depositors are terminating their demand deposit in advance, ahead of their consumption needs. Under such circumstances, rational depositors would withdraw their fund to avoid being the last to do so and suffer a loss from the sale of the long-term assets.

This negative perception on the bank may turn into a self-fulfilling prophecy as the large liquidity shock may cause insolvency problems for an otherwise solvent bank. Hence, although bank runs are individually rational, the outcome of such action may lead to social inefficiency when information on bank assets does not reflect fundamentals.

Furthermore, a run on one bank may precipitate a run on other banks when depositors believe that the failure of the bank signals difficulties throughout the banking system, which creates aggregate liquidity shortage (Aghion, Bolton and Dewatripont, 2000; Diamond and Rajan, 2005). Consequently, solvent banks in the system may also have to liquidate their assets at loss to meet liquidity demand, leading to insolvency problems in an otherwise solvent banking system.

Concerning information-based bank runs, the hypothesis posits that depositors have imperfect information on the true state of the assets of their bank, exposing them to the signal-extraction problem. Although some depositors have private information on the prospect of banks' assets, others are uninformed and make inferences based on observable indicators. These indicators may include information on the number of withdrawals at their bank and negative information on other banks.

Chari and Jagannathan (1988) develop a model in which bank runs occur due to uninformed depositors' misinterpretation of liquidity-motivated withdrawals as information-driven withdrawals. In particular, uniformed depositors lack information on the actual proportion of informed withdrawers. Although they might observe the number of withdrawals, they have incomplete information on the withdrawers itself. In particular, they are unable to distinguish between withdrawers that acted based on private adverse signals and those who withdrew due to idiosyncratic liquidity shocks. When the random realisation of withdrawals is unusually large, uniformed depositors may misinterpret the withdrawals as a negative signal on the bank and precipitate a run.

Furthermore, the noise that precipitates the run may eventually spillover to other banks. This occurs when depositors believe the adverse information attributed to the bank also implies adverse information on other banks, in particular those with common financial characteristics (Aharony and Swary, 1996; Chen, 1999).

Levy-Yeyati, Martínez Pería and Schmukler (2010) suggest that macroeconomic factors may also explain the large runs observed during crises periods. The effect of macroeconomic factors unrelated to bank fundamentals can occur when worsening macroeconomic conditions threaten deposit value. For example, when the expected return on deposits is lower than that from holding foreign currency, and currency conversion is not an option, depositors might withdraw their funds. Consequently, aggregate liquidity shocks and bank panics are more likely to occur during macroeconomic crises. The finding is also similar to that of Adams, Füss and Gropp (2014). They find empirical evidence that the magnitude and the duration of spillover among financial institutions is conditional on the state of the market. A shock that has a small effect in normal times may lead to a considerable spillover effect during volatile market periods.

Bank runs can be avoided if depositors have confidence in the prospects of their bank assets. Financial safety nets, in particular deposit insurance schemes, have been introduced to mitigate the coordination failure which may result in pure-panic bank runs. Chen (1999) argues that deposit insurance can induce depositors to be more patient in responding to information. Because insured uniformed depositors have less incentive to start a bank run, uninsured informed depositors can always wait until the the true state of their bank is revealed. Hence, countries with a deposit insurance scheme should no longer experience bank panics.

However, the global financial crisis of 2008 provides an example of a modern bank run. Unlike traditional bank runs in which depositor behaviour triggers a run, the recent crisis demonstrates the vulnerability of uninsured wholesale funds to run (Rochet and Vives, 2004; Huang and Ratnovski, 2011; Gorton and Metrick, 2012). Asymmetric information exposes these creditors to noise on the future realisation of banks' assets return. In addition, the response of other creditors imposes payoff externality. Hence, the decision to liquidate their claim on the bank depends not only on their private information but also their observation of the actions of other creditors.

Coordination failure in modern banks arises when the withdrawals of several creditors based on private adverse information coincide with the withdrawals of others, who are driven by idiosyncratic liquidity shocks. When the random realisation of both events is large, the withdrawals may create a liquidity problem. To meet the liquidity demand, the bank borrows from the secondary market, pledging their assets at a fire-sale premium. This is akin to the liquidation of long-term illiquid assets in a traditional bank run. The high cost of borrowing reduces the future realisation of the banks' assets return, which in turn increases the likelihood of bank failure. Due to incomplete information, the remaining creditors are uncertain whether others will choose to rollover or liquidate their claims. To avoid being the last to withdraw their funds, rational creditors follow the herd, disregarding their own private information.

In modern bank runs, the problem of asymmetric information is exacerbated by the increased complexity in bank network and activities. Caballero and Simsek (2013) provide a model in which the complexity of financial interconnectedness among banks increases uncertainty during a financial turmoil. Due to network complexity, a bank has information on its' direct exposure but are uncertain about its' indirect exposure to banks that are peripheral in the bank's network. Therefore, the lack of information on cross exposure increases the uncertainty on the state of their direct exposure. The problem is more severe during financial crises when the spillover effect from indirect linkages is more likely. Accordingly, banks may prefer to hoard liquidity in a crisis, which in turn may worsen the condition of the banking system.

Furthermore, financial innovations have led to the introduction of a large number of new financial instruments. Among these are: asset-backed securities; credit default swaps (CDS) and collateralised loan obligations. The proliferation of these complex financial securities, which are opaque and difficult to value, exposes investors to asymmetric information problem and, therefore, exacerbates liquidity risk in the financial system. Hence, similar to traditional banks, modern banks are prone to confidence crises and bank runs (Flannery, Kwan and Nimalendran, 2013).[13]

3.3.3. Systemic Risk Taking: Herding Leading to Systemic Risk

Benoit *et al.* (2017) propose a category of literature that focuses on systemic risk taking. This strand of literature studies why financial institutions choose to be exposed to similar risks, reinforcing the channels explained in section 3.3.2 of this chapter.

As discussed in the first empirical chapter ("Bank Herding and its Determinants"), Acharya and Yorulmazer (2007) show that banks have the incentive to invest in the same industry to increase the likelihood of a collective bailout position should default occur. They also suggest that the too-many-to-fail problem is more relevant for small banks compared to large banks. Farhi and Tirole (2012) also argue that systemic risk can arise from strategic complementarities among banks on their liability side. Banks, due to the likelihood of a collective bailout, are motivated to herd in terms of maturity mismatch. Hence, their theoretical prediction complements that of Acharya and Yorulmazer (2008), who posit that banks herd through common investments.

Consistent with both studies, to increase the likelihood of a collective bailout position should default occur, banks synchronise their assets allocation and funding strategies. This in turn reinforces the balance sheet channel and information channel of systemic risk discussed in the previous section (3.3.2. Propagation Channels). Hence, herding increases systemic risk in the banking system.

[13] Investment banks are more actively involved in the issuance and trading of these securities. Nonetheless, several commercial banks such as Citigroup, J.P. Morgan and Bank of America also play a role in the packaging and reselling of these securities, supplementing traditional banking activities (Gorton and Metrick, 2012).

3.3.4. Systemic Risk Measurement

According to Amini and Minca (2012), systemic risk can be modelled using two different approaches. The first approach is represented by the reduced form models. This approach treats financial institutions as entities within a portfolio. Market information, such as stock return and CDS spreads, is used to measure systemic risk. Another approach is the structural models. The purpose of this method is to provide a topology of the financial system as a network of counterparties with interconnected balance sheets. Simulations are subsequently used to measure the impact of a selected number of banks defaulting in the network. Hence, the approach requires a considerable set of information on banks' balance sheet and the interrelations between these balance sheets.

Mertzanis (2014) argues that network analysis reflects the stylized facts in the financial markets better compared to traditional financial models. The reliance of the latter model on the assumption of normal distribution of financial returns creates a difficult task for the statistic modelling of several anomalies in financial time series. These include volatility clustering and leverage effect. However, Mertzanis (2014) also shows that structural models have their own weaknesses. In particular, these models lack theoretical underpinnings and robust empirical testing. Upper (2011) also argues that simulations may generate inaccurate and misleading results when they are based on weak behavioural foundations or use undeveloped behaviour assumptions.

Concerning financial models' deficiencies, several reduced form models have accounted for the presence of anomalies in financial data in their computation. In particular, ΔCoVaR uses non-parametric quantile regression and SRISK accounts for volatility clustering and leverage effect based on asymmetric GARCH and time-varying correlation. As this study focuses on the empirical testing of a hypothesis, financial models may be more relevant for measuring systemic risk.

Within the reduced form models, several systemic risk measures have been proposed. These measures are based on the assumption that, if markets are efficient, the current market prices of the securities should reflect market information related to the financial institutions (Krainer and Lopez, 2004; Gropp, Vesala and Vulpes, 2006). In addition, compared to measures based on accounting data, these measures may detect systemic risk in a much timely manner.

Laeven, Ratnovski and Tong (2016) suggest two market-based systemic risk measures that are widely used and established: ΔCoVaR (Adrian and Brunnermeier, 2016) and SRISK (Brownlees and Engle, 2017). Adrian and Brunnermeier (2016) propose ΔCoVaR as a systemic risk measure and use U.S. bank holding companies as a sample in their study. They find that leverage, size, maturity mismatch, and asset price booms significantly predict systemic risk. Using the same measure, López-Espinosa *et al.* (2012) find short-term wholesale funding as a key determinant of systemic risk and weak evidence of size and leverage as factors that contribute to systemic risk.

Furthermore, Laeven, Ratnovski and Tong (2016) use both ΔCoVaR and SRISK to identify bank-specific factors that determine the significant variation in the cross-section systemic risk of large banks during the 2008 Global Financial Crisis. Using large banks with assets in excess of USD 10 billion from 56 countries, they find strong evidence that systemic risk increases with bank size and is inversely related to bank capital. In addition to both measures, Cai *et al.* (2018) use DIP (Huang, Zhou and Zhu, 2009) to measure the impact of interconnectedness due to loan syndication in the U.S.

market. They find that bank interconnectedness is driven mainly by diversification efforts and is positively correlated with systemic risk.

3.3.5. The Gap in the Literature and the Contributions

1. Gap in the Literature

As discussed in section 3.3.2 of this chapter, theoretical work on systemic risk has shown that bank interconnectedness can increase systemic risk through different channels of financial contagion. Several studies have also argued that financial institutions may choose to be exposed to similar risks, reinforcing the propagation channels of systemic risk (Acharya and Yorulmazer, 2007; Farhi and Tirole, 2012). Accordingly, empirical research on the systemic risk implications of bank herding is necessary to shed some light on the issue. Several empirical studies on herding exist. Nonetheless, they emphasise more the methods for detecting herding and have not analysed empirically the relationship between systemic risk and herding (Jain and Gupta, 1987; Barron and Valev, 2000; Uchida and Nakagawa, 2007).

Benoit *et al.* (2017) survey 220 published studies on systemic risk, covering 35 years. Based on their assessment of the vast literature, they identify two main clusters and the gap between them. The first strand of literature studies a specific propagation channel of systemic risk. This includes research on direct linkage from interbank credit exposure and indirect linkages arising from exposure to common assets, as explained in section 3.3.2 of this chapter. Although these studies commonly propose methods to identify financial institutions that are central in a network, they rarely provide a concrete linkage between the methods and the relevant prudential measures to mitigate the risk. This limits the applicability of these studies in terms of policy implementations.

The second category of literature is that related to systemic risk measurement, which is discussed in section 3.3.4 of this chapter. The literature proposes methods for measuring systemic risk. Nonetheless, these studies take a broad, multi-channel approach to systemic risk and focus more on identifying key individual bank vulnerabilities that determine systemic risk. For example, López-Espinosa *et al.* (2012) and Adrian and Brunnermeier (2016) relate ΔCoVaR to leverage, size and reliance on wholesale funds.

Individual bank vulnerabilities alone, however, may not necessarily pose a systemic risk. De Bandt and Hartmann (2000) suggest three interrelated aspects which affect financial systems' vulnerability to systemic risk: (a) balance sheets structure or individual bank vulnerabilities; (b) financial institutions' interconnectedness; and (c) market expectations. This highlights the importance for the researcher of considering bank interconnectedness, in addition to individual bank vulnerabilities, when analysing and proposing policies to mitigate systemic risk.

2. Contributions to Existing Literature

Several studies related to herding and systemic risk exist. Nonetheless, as explained in the previous section ("Gap in the Literature"), there are still important gaps that must be addressed. This study contributes towards in bridging the gaps in the existing literature in several ways. First, it provides an empirical assessment of systemic risk taking by banks through herding (Acharya and Yorulmazer, 2007; Farhi and Tirole, 2012). Therefore, this study fills the void in existing literature on herding which focus more on methods to detect herding.

Second, this research improves systemic risk analyses by relating bank interconnectedness from herding to systemic risk measurements. Studies related to systemic risk measurement do not commonly identify the propagation channels explicitly (Benoit *et al.*, 2017). Accordingly, the inclusion of herding will further capture the overall dimension of systemic risk.

Third, this chapter proposes relevant macroprudential instruments for mitigating systemic risk related to herding. Benoit *et al.* (2017) emphasise the importance of having regulations that deter herding, arguing that herding is one of the challenging issues that must be addressed by systemic risk regulation.

Laeven, Ratnovski and Tong (2016) and Cai *et al.* (2018) relate the potential factors of systemic risk to different measures of systemic risk. This study, however, differs from Laeven, Ratnovski and Tong (2016) in the sense that they focus on bank size as the determinant of systemic risk. However, this study proposes herding as a systemic risk factor, controlling for bank size in addition to other known determinants of systemic risk. In addition, they use large international financial institutions as their sample, whereas this study covers a larger dataset, comprised of cross-country publicly listed commercial banks.

Cai *et al.* (2018) study systemic risk from bank interconnectedness in a syndicated loan portfolio. Hence, this study is different from theirs, as it provides a broader perspective on the mechanism by which banks are interconnected to increase systemic risk. In particular, instead of being limited to specific banking activities, herding in this study involves imitation in both asset allocation and funding strategies. Moreover, the findings of Cai *et al.* (2018) are related to the interconnectedness that arises due to negative externalities from diversification strategy (Wagner, 2010; Ibragimov, Jaffee and Walden, 2011). However, this study focuses on increased interconnectedness as a consequence of banks' active engagement in systemic risk taking through herding, as described in Acharya and Yorulmazer (2007) and Farhi and Tirole (2012). Another difference is that their study focuses on the U.S. syndicated loan market, whereas this study provides a cross-country study on bank interconnectedness.

3.4. Methodology

The relationship between systemic risk and herding is represented by a panel-data model in the following functional form:

Systemic risk = f(interactions between herding and individual bank vulnerabilities, individual bank vulnerabilities, control variables)

As proxies for systemic risk, this study uses Conditional Value at Risk (ΔCoVaR), as proposed by Adrian and Brunnermeier (2016), and SRISK (Acharya *et al.*, 2012; Brownlees and Engle, 2017) to capture different aspects of systemic risk. ΔCoVaR measures the Value at Risk (VaR) of the overall banking system because of the distress of an individual bank, and SRISK measures the expected capital shortfall of an individual bank resulting from a severe systematic shock. The computation of both systemic risk measures is explained in section 3.5.2 of this chapter.

Within transformation is used to estimate the parameters for ΔCoVaR in the presence of unobserved bank-specific fixed effects, using the following model:

$$y_{i,t} - \bar{y}_i = (\boldsymbol{x}_{i,t-1} - \bar{\boldsymbol{x}}_i)'\boldsymbol{\beta} + \left(v_{i,t} - \bar{v}_i\right) \qquad (3.1)$$

Where $\bar{y}_i = \frac{1}{T}\sum_{t=1}^{T} y_{i,t}$, $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{i,t}$, and $\bar{v}_i = \frac{1}{T}\sum_{t=1}^{T} v_{i,t}$. $y_{i,t}$ is the dependent variable or systemic risk. $\boldsymbol{x}_{i,t-1}$ is a k dimensional vector of the first lag of the time-variant explanatory variables and for any *t*, $\boldsymbol{x}_{i,t-1} \sim$ *i.i.d.* across individual bank *i*. $v_{i,t}$ is the error term. For any *t*, *s*, $v_{i,t}$ is independent of $v_{j,s}$ when i ≠j. Year fixed effects are included in the regression to control for unobserved time effects.

Furthermore, a different estimation method is used for SRISK. By imposing the definition of SRISK and using log transformation to narrow the range of the SRISK value, banks with zero and negative SRISK are excluded from the sample. Hence, to improve the generalisation of the result, truncated regression is used to estimate the parameters for SRISK. The regression has the following form:

$$E\left[y_{i,t} \middle| y_{i,t} > l\right] = \boldsymbol{x}'_{i,t-1}\beta + \sigma \frac{\phi[\frac{\left(l - \boldsymbol{x}'_{i,t-1}\beta\right)}{\sigma}]}{1 - \Phi[\frac{\left(l - \boldsymbol{x}'_{i,t-1}\beta\right)}{\sigma}]} \qquad (3.2)$$

Where $\boldsymbol{x}_{i,t-1}$ is a k dimensional vector of the first lag of the time-variant explanatory variables and for any *t*, $\boldsymbol{x}_{i,t-1} \sim$ *i.i.d.* across individual banks, l is a constant, and $\phi[.]$ and $\Phi[.]$ are each the standard normal probability density functions and cumulative density functions.

The MLE is used to derive the estimators for the model. The MLE estimator maximises the log-likelihood function of the non-linear joint density function of independent and identically distributed bank-level observations, as follows:

$$\widehat{\boldsymbol{\beta}}_{MLE} = \underset{\beta}{arg\,max} - \frac{NT}{2} log[2\pi\sigma^2] - \frac{1}{2\sigma^2} \sum_{t=1}^{T}\sum_{i=1}^{N}\left[\boldsymbol{y}_{i,t} - \boldsymbol{x}_{i,t-1}\boldsymbol{\beta}\right]^2 -$$

$$\sum_{t=1}^{T}\sum_{i=1}^{N} log\left\{1 - \Phi[\frac{(l-x'_{i,t-1}\beta)}{\sigma}]\right\} \qquad (3.3)$$

Both bank fixed effects and year fixed effects are included in the regression to control for unobserved bank-specific fixed effects and unobserved time effects, respectively. In addition, the standard errors for both models are adjusted for within-group correlation, clustered at the country level to address heteroscedasticity.

3.5. Data

3.5.1. Sample

The sample includes publicly listed commercial banks across different countries that were active in 2013–2017. Banks not publicly listed are excluded because both systemic risk measures are based on stock return. The sample for ΔCoVaR consists of 2,804 bank-year data, covering 600 banks from 46 countries within a 5-year observation period. The sample for SRISK consists of 3,160 bank-year data, covering 721 banks from 81 countries with the same observation period.

The sample for ΔCoVaR is smaller compared to that for SRISK, because a minimum number of banks within a country is required to compute ΔCoVaR. Unlike SRISK, which measures systemic risk based on individual bank capital shortfall, ΔCoVaR measures the VaR of the overall banking system as a result of the distress of a particular bank. Accordingly, the measure is sensitive to the variation of banks included in the sample.

Considering that the sample consists of only listed banks, and to provide a sufficient representation of the banking system within a specific country, a country is required to have at least five banks to be included in the sample. The minimum number of banks is consistent with the first empirical chapter (”Bank Herding and its Determinants”) and similar to other cross-country studies on banking. In particular, Berger, Klapper and Turk-Ariss (2009) requires a country to have at least five active banks and Anginer, Demirguc-Kunt and Zhu (2014b) exclude countries with fewer than seven banks.

3.5.2. Systemic Risk Measures

Two recently and commonly applied measures of systemic risk are used as proxies for systemic risk, ΔCoVaR (Adrian and Brunnermeier, 2016) and SRISK (Brownlees and Engle, 2017). Both measures capture different aspects of systemic risk (Laeven, Ratnovski and Tong, 2016; Cai *et al.*, 2018). ΔCoVaR measures the VaR of the overall banking system as a result of the distress of a particular bank, whereas SRISK measures the expected capital shortfall of a specific bank as a consequence of a severe systematic shock. More precisely, SRISK measures bank vulnerabilities to systematic shock and the estimated capital shortfall that a bank needs to meet to comply with regulatory capital requirements. As an indicator of system distress, SRISK uses a cumulative stock market decline of 40% within a 180-day period.

Furthermore, ΔCoVaR is estimated using weekly data and SRISK is estimated using daily data (Adrian and Brunnermeier, 2016; Laeven, Ratnovski and Tong, 2016; Brownlees and Engle, 2017). To compute both measures, recursive sampling is applied using data from January 2000 to include the Global Financial Crisis of 2008. The starting period is similar to that of Laeven, Ratnovski and Tong (2016).

1. ΔCoVaR

ΔCoVaR, as proposed by Adrian and Brunnermeier (2016), uses stock market data to estimate systemic risk. ΔCoVaR measures the externality that an individual bank imposes on the banking system. Following Laeven, Ratnovski and Tong (2016), the average of the predicted ΔCoVaR over the related observation year is used as the dependent variable. The computation of ΔCoVaR involves several variables and steps.

First, the market loss associated with a given bank *i* at time *t* is defined by:

$$X_t^i = \frac{V_t^i - V_{t-1}^i}{V_{t-1}^i} \qquad (3.4)$$

Where V_t^i denotes the market value of equity of bank *i*. Following Adrian and Brunnermeier (2016), banks are required to have at least 260 weeks of market equity returns data to be included in the sample. Furthermore, the loss associated with the banking system is defined by:

$$X_t^{sys} = \frac{V_t^{sys} - V_{t-1}^{sys}}{V_{t-1}^{sys}} \qquad (3.5)$$

Where $V_t^{sys} = \sum_i V_t^i$

The next step is to define VaR, which represents the minimum loss that an individual bank is likely to occur given a certain confidence level q. Following Adrian and Brunnermeier (2016) and Laeven, Ratnovski and Tong (2016), q is set at 5%. The unconditional VaR for the individual bank, VaR_q^i is defined as the threshold in which the probability X_t^i above the threshold is q-quantile:

$$Pr\left(X_t^i \geq VaR_q^i\right) = q \qquad (3.6)$$

The unconditional VaR of the system is defined by:

$$Pr\left(X_t^{sys} \geq VaR_q^{sys}\right) = q \qquad (3.7)$$

In addition, conditional VaR or CoVaR, which measures bank *i*'s contribution to VaR of the banking system, is defined by:

$$Pr\left(X_t^{sys} \geq CoVaR_q^{sys|X_t^i = VaR_q^i}\right) = q \qquad (3.8)$$

$\Delta CoVaR_q^i$, which is the difference between CoVaR when bank *i* is in distress (VaR_q^i) and when under normal conditions (VaR_{50}^i), measures the externality that the underlying bank imposes on the banking system:

$$\Delta CoVaR_q^i = CoVaR_q^{sys|X_t^i=VaR_q^i} - CoVaR_q^{sys|X_t^i=VaR_{50}^i}$$

$$= \hat{\beta}_q^{sys|X_t^i=VaR_q^i}\left(VaR_q^i - VaR_{50}^i\right) \qquad (3.9)$$

To generate time-varying $\Delta CoVaR_{q,t}^i$, indicated with a subscript *t*, a set of conditioning global state variables are used. More precisely, time-varying $CoVaR_{q,t}^i$ and $VaR_{q,t}^i$, are estimated conditional on a vector of lagged global state variables M_{t-1}. The parameters for both, the time-varying $VaR_{q,t}^i$ and $CoVaR_{q,t}^i$, are estimated using the following quantile regressions:

$$X_t^i = \alpha_q^i + \gamma_q^i M_{t-1} + \varepsilon_{q,t}^i \qquad (3.10)$$

$$X_t^{sys|i} = \alpha_q^{sys|i} + \gamma_q^{sys|i} M_{t-1} + \beta_q^{sys|i} X_t^i + \varepsilon_{q,t}^{sys|i} \qquad (3.11)$$

The predicted values from equations (3.10) and (3.11) are subsequently used to obtain:

$$VaR_{q,t}^i = \hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-1} \qquad (3.12)$$

$$CoVaR_{q,t}^{sys|X_t^i=VaR_q^i} = \hat{\alpha}_q^{sys|i} + \hat{\gamma}_q^{sys|X_t^i=VaR_q^i} M_{t-1} + \hat{\beta}_q^{sys|X_t^i=VaR_q^i} VaR_{q,t}^i \qquad (3.13)$$

Furthermore, time-varying $\Delta CoVaR_{q,t}^i$ is computed in the following form:

$$\Delta CoVaR_{q,t}^i = CoVaR_{q,t}^{sys|X_t^i=VaR_q^i} - CoVaR_{q,t}^{sys|X_t^i=VaR_{50}^i}$$

$$= \hat{\beta}_q^{sys|X_t^i=VaR_q^i}\left(VaR_{q,t}^i - VaR_{50,t}^i\right) \qquad (3.14)$$

Following Adrian and Brunnermeier (2016) and Laeven, Ratnovski and Tong (2016), the global state variables M_{t-1} include:

1. The VIX index of stock market volatility;

2. The change in the 3-month Treasury bill rate;
3. The liquidity spread measured by the short-term TED spread, which is the difference between the three-month LIBOR rate and the three-month Treasury bill rate;
4. The change in the slope of the yield curve; and
5. The change in the credit spread between BAA-rated bonds and the Treasury rate.

Although the set of state variables sampled from the U.S. market is used as common conditioning variables, the approach is considered reasonable because of the strong degree of globalisation in the financial industry and the predominance of the U.S. economy (López-Espinosa *et al.*, 2012).

Furthermore, data on global state variables to compute time-varying ΔCoVaR are collected from different publicly available data sources, as follows:

1. The VIX index of stock market volatility from the Chicago Board Options Exchange (CBOE);
2. The change in the three-month Treasury bill rate from the Federal Reserve Economic Data;
3. The TED spread from the Federal Reserve Economic Data;
4. The change in the slope of the yield curve, measured by the spread between the 10-year Treasury constant maturity rate from the Federal Reserve Board's H.15 release and the 3-month Treasury bill rate from the Federal Reserve Economic Data; and
5. The change in the credit spread between Moody's Baa-rated bonds and the 10-year Treasury rate from the Federal Reserve Economic Data.

As discussed earlier in this section, quantile regression is used to estimate the parameters in equations (3.10) and (3.11) respectively. The quantile regression estimator is the estimator which minimises the sum of the absolute residuals, weighted asymmetrically by a function that depends on the q-quantile. Koenker and Bassett (1978) propose the following representation:

$$\widehat{\boldsymbol{\beta}}_q = \frac{min}{\beta}\left[\sum_{t:y_t \leq f(x_t,\beta)} q|y_t - f(x_t,\beta)| + \sum_{t:y_t > f(x_c,\beta)} (1-q)|y_t - f(x_t,\beta)|\right] \quad (3.15)$$

2. SRISK

SRISK, as proposed by Acharya, Engle and Richardson (2012) and Brownlees and Engle (2017), measures the expected capital shortfall of an individual bank conditional on a crisis affecting the whole banking system. SRISK is defined as:

$$SRISK_{i,t} = E_t\left(CS_{i,t+h} \middle| R_{m,t+1:t+h} < C\right)$$
$$= kE_t\left(D_{i,t+h} \middle| R_{m,t+1:t+h} < C\right) - (1-k)E_t\left(V_{i,t+h} \middle| R_{m,t+1:t+h} < C\right) \quad (3.16)$$

Where $R_{m,t+1:t+h}$ is the multi period arithmetic market return between period *t + 1* and *t + h* – following Acharya, Engle and Richardson (2012), *h* is set at 180 days – *C* is the systemic event; $V_{i,t+h}$ is the market value of equity *h* horizon in the future; D_{it+h} is the book value of debt; and *k* is the prudential capital requirement which is set to 8% for U.S. banks and 5.5% for banks that operate under IFRS (Engle, Jondeau and Rockinger, 2015; Cai *et al.*, 2018).

Following Laeven, Ratnovski and Tong (2016), market value of equity is measured in millions of USD. Data related to market return and market value of equity are both collected from Datastream. As data on market value of equity from Datastream are in its original currencies, the data are converted to USD using exchange rate data extracted from the same database. In addition, the book value of debt is measured by bank liabilities. Data on the variable are obtained from Orbis Bank Focus.

Brownlees and Engle (2017) argue that during a crisis, capital surpluses are unlikely to be easily transferred through mergers or loans to support failing banks and reduce systemic risk. Thereby, capital surpluses are less meaningful in terms of systemic risk and SRISK is limited from a positive value to zero:

$$SRISK_i = (SRISK_i)_+ \text{ and } (x)_+ \text{ denotes } \max(x, 0) \qquad (3.17)$$

Log transformation is further used to narrow the range of the SRISK value.

Moreover, assuming that in the event of a systemic crisis, debt cannot be renegotiated, $E_t\left(D_{i,t+h} \middle| R_{m,t+1:t+h} < C\right) = D_{i,t}$ and:

$$\begin{aligned} SRISK_{i,t} &= kD_{i,t} - (1-k)V_{i,t}\left(1 - LRMES_{i,t}\right) \\ &= V_{i,t}\left[kL_{i,t} + (1-k)LRMES_{i,t} - 1\right] \qquad (3.18) \end{aligned}$$

Where $L_{i,t}$ denotes the quasi leverage ratio $\frac{D_{i,t}+V_{i,t}}{V_{i,t}}$ and $LRMES_{i,t}$ is the Long Run MES, which is the expectation of the equity multi period arithmetic return conditional on the systemic event:

$$LRMES_{i,t} = -E_t\left(R_{i,t+1:t+h} \middle| R_{m,t+1:t+h} < C\right) \qquad (3.19)$$

To compute LRMES, an approximation based on one-day MES is used (Acharya, Engle and Richardson, 2012; Laeven, Ratnovski and Tong, 2016):

$$LRMES_{i,t} = 1 - \exp\left(-18 \times MES_{i,t}\right) \qquad (3.20)$$

Following Laeven, Ratnovski and Tong (2016), SRISK is computed using the daily average of the predicted values for MES over the related year observation. MES is estimated by specifying a model for the market returns and individual bank returns. The bivariate process of market and individual bank returns is as follows:

$$r_{m,t} = \sigma_{m,t}\varepsilon_{m,t} \qquad (3.21)$$

$$r_{i,t} = \sigma_{i,t}\varepsilon_{i,t} = \sigma_{i,t}\left(\rho_{im,t}\varepsilon_{m,t} + \sqrt{1-\rho_{im,t}^2}\xi_{i,t}\right) \qquad (3.22)$$

Where $(\varepsilon_{m,t}, \xi_{i,t}) \sim F$; $\varepsilon_{m,t}$ and $\varepsilon_{i,t}$ denotes the error terms for market returns and individual bank returns; $\xi_{i,t}$ denotes idiosyncratic shocks; $r_{m,t} = log(1 + R_{m,t})$ and $r_{i,t} = log(1 + R_{i,t})$ are the logarithmic stock return of the market and individual bank i ; $\sigma_{m,t}$ and $\sigma_{i,t}$ are the volatilities of the market and individual bank *i* return at time *t* respectively; $\rho_{im,t}$ denotes the time-varying correlation between $\varepsilon_{i,t}$ and $\varepsilon_{m,t}$.

From the bivariate models, MES can be defined as:

$$MES_{i,t-1} = -E_{t-1}(r_{i,t}|r_{m,t} < C) \qquad (3.23)$$

$$= -\sigma_{i,t}\left[\rho_{im,t}E_{t-1}\left(\varepsilon_{m,t} < \frac{c}{\sigma_{m,t}}\right) + \sqrt{1-\rho_{im,t}^2}E_{t-1}\left(\xi_{i,t} < \frac{c}{\sigma_{m,t}}\right)\right]$$

Where following Laeven, Ratnovski and Tong (2016), *C* is the threshold of a 2% decline in market index.

Furthermore, Brownlees and Engle (2017) opt to use an asymmetric GARCH model to estimate the time-varying volatilities of the error terms, $\sigma_{m,t}$ and $\sigma_{i,t}$, and the Dynamic Conditional Correlation (DCC) method is used to estimate the time-varying correlation, $\rho_{i,t}$. In addition, the tail expectations are estimated using non-parametric distribution and smoothened using a kernel estimator (Idier,Lamé and Mésonnier, 2014).

Concerning time-varying volatilities, Brownlees and Engle (2017) estimate the variable using a GJR–GARCH volatility model in the following form:

$$\sigma_{m,t}^2 = \omega_m + \alpha r_{m,t-1}^2 + \gamma r_{m,t-1}^2 I(r_{m,t-1} < 0) + \beta_m \sigma_{m,t-1}^2 \qquad (3.24)$$

$$\sigma_{i,t}^2 = \omega_i + \alpha r_{i,t-1}^2 + \gamma r_{i,t-1}^2 I(r_{i,t-1} < 0) + \beta_i \sigma_{i,t-1}^2 \qquad (3.25)$$

The model accounts for the possible asymmetries of the impact of negative information on conditional volatility.

The empirical analysis of Brownlees and Engle (2017) focuses on a panel of large U.S financial firms. However, the current study uses a wider set of sample, covering cross-country listed commercial banks, not limited to large ones. Hence, to capture the broader stylised facts of individual bank stock return, GARCH (1,1) is used in addition to GJR–GARCH. Several studies have also used GARCH (1,1) arguing that the model provides the most appropriate representation of the conditional volatility process in the market (Billio *et al.*, 2012; Boffelli, 2016).

To estimate the time-varying correlation of the error terms, $\varepsilon_{i,t} = \frac{r_{i,t}}{\sigma_{i,t}}$ and $\varepsilon_{m,t} = \frac{r_{m,t}}{\sigma_{m,t}}$, the DCC method is used, whereby the time-varying correlation matrix is defined as:

$$\boldsymbol{R}_{im,t} = \begin{bmatrix} 1 & \rho_{im,t} \\ \rho_{im,t} & 1 \end{bmatrix} = diag(\boldsymbol{Q}_{im,t})^{-\frac{1}{2}}\boldsymbol{Q}_{im,t}diag(\boldsymbol{Q}_{im,t})^{-\frac{1}{2}} \tag{3.26}$$

Furthermore, $\boldsymbol{Q}_{im,t}$ denotes the pseudo-correlation matrix in the following form:

$$\boldsymbol{Q}_{im,t} = (1-\alpha-\beta)\boldsymbol{s}_i + \alpha \begin{bmatrix} \varepsilon_{i,t-1} \\ \varepsilon_{m,t-1} \end{bmatrix} \begin{bmatrix} \varepsilon_{i,t-1} \\ \varepsilon_{m,t-1} \end{bmatrix}' + \beta \boldsymbol{Q}_{im,t-1} \tag{3.27}$$

Where α and β are scalars; $\alpha > 0$; $\beta > 0$; $\alpha + \beta < 1$; and $\boldsymbol{s}_i$ denotes the unconditional correlation matrix of the market and individual bank adjusted returns and estimated empirically as $\widehat{\boldsymbol{s}_i} = \frac{1}{T}\sum_{t=1}^{T} \begin{bmatrix} \varepsilon_{i,t} \\ \varepsilon_{m,t} \end{bmatrix} \begin{bmatrix} \varepsilon_{i,t} \\ \varepsilon_{m,t} \end{bmatrix}'$.

On the estimation of the tail expectations, a non-parametric kernel density estimation approach is used, as follows:

$$E_{t-1}\left(\varepsilon_{m,t} \middle| \varepsilon_{m,t} < \frac{c}{\sigma_{m,t}}\right) = \frac{\sum_{t=1}^{T-1} \varepsilon_{m,t} K_h\left(\varepsilon_{m,t} - \frac{c}{\sigma_{m,t}}\right)}{\sum_{t=1}^{T-1} K_h\left(\varepsilon_{m,t} - \frac{c}{\sigma_{m,t}}\right)} \tag{3.28}$$

$$E_{t-1}\left(\xi_{i,t}\middle|\varepsilon_{m,t} < \frac{c}{\sigma_{m,t}}\right) = \frac{\sum_{t=1}^{T-1} \xi_{i,t} K_h\left(\varepsilon_{m,t} - \frac{c}{\sigma_{m,t}}\right)}{\sum_{t=1}^{T-1} K_h\left(\varepsilon_{m,t} - \frac{c}{\sigma_{m,t}}\right)} \tag{3.29}$$

Where $K_h(j) = \int_{-\infty}^{\frac{j}{h}} k(x)dx$ is the kernel density estimate; *k(x)* denotes a kernel function; and h is the smoothing parameter. Following Idier, Lamé and Mésonnier (2014), the estimation algorithm is initialised using Gaussian kernel, $k(x) = \frac{1}{\sqrt{2\pi}} e^{\frac{-x^2}{2}}$, and the tail expectations are estimated using recursive samples.

3.5.3. The Interaction between Herding and Individual Bank Vulnerabilities

Several related studies have argued that systemic risk taking reinforces the propagation channels of systemic risk (Acharya and Yorulmazer, 2007; Farhi and Tirole, 2012; Benoit *et al.*, 2017). Accordingly, by strengthening these channels, herding is expected to amplify the effect of individual bank vulnerabilities on systemic risk. The amplification effect is measured as the interaction between herding and individual bank vulnerabilities on systemic risk. This implies that banks that herd have a steeper slope or a higher effect of individual bank vulnerabilities on systemic risk per unit increase in vulnerabilities compared to other banks in the industry. The bank-level herding measures and the related individual bank vulnerabilities are explained in the following discussion.

1. Bank-Level Herding Measures

This chapter proposes to measure the extent of herding using the method described in the first empirical chapter ("Bank Herding and its Determinants"). Nonetheless, further adjustment is applied to reflect individual bank-level herding. In particular, the DGC in this chapter is redefined and two measures are used to capture different aspects of herding. The first measure, DGC Leader, captures the extent of herding or mimicking of bank *i* by other banks *j*, or bank *i* acting as the leader in the herd. The measure is computed as the fraction of statistically significant $\beta_{j,i}$ among $N-1$ relationships in the following form:

$$DGC\ Leader \equiv \frac{1}{N-1}\sum_{j=1}^{N-1}(i \to j) \qquad (3.30)$$

The second, DGC Follower, captures the extent of herding or mimicking of other banks *j* by bank *i*, or bank *i* acting as follower in the herd. The measure is computed as the fraction of statistically significant $\beta_{i,j}$ among $N-1$ relationships in the following form:

$$DGC\ Follower \equiv \frac{1}{N-1}\sum_{j=1}^{N-1}(j \to i) \qquad (3.31)$$

Consistent with the first empirical chapter, the measure excludes relationships with feedback effects.[14] As discussed in chapter 2 ("Bank Herding and its Determinants"), Granger's procedure involves running a regression in the form of equation (2.16) and (2.17). In addition, the method uses adjusted stock return to control for heteroscedasticity as the dependent variable in the form of equation (2.18).

Furthermore, the log transformation of the herding measures is used in the interaction terms. This provides an intuitive interpretation of the relationship between systemic risk and bank interconnectedness from herding. In particular, the marginal

[14] As explained in the first empirical chapter ("Bank Herding and its Determinants"), consistent with the definition of herding in this study, a one-way test is used to reduce the possibility of identifying spurious herding as active herding. Jain and Gupta (1987) argue that the two-way test may indicate several possibilities: (i) there is a feedback effect in which both banks consider each other behaviours when making lending decisions and (ii) the lending or investment decisions are the result of similar credit or business analysis approach. The latter, however, does not necessarily indicate the existence of herding.

effect on systemic risk of an additional unit of connection declines when a bank is already largely connected with other banks in the banking system. As the number of connections between bank i and other banks j_N increases, it is more likely bank i is connected with bank j_1 and j_2, in which bank j_2 is also connected with bank j_1. Hence, when bank j_1 fails as a result of the failure of bank *i*, bank j_2 is likely to fail irrespective of whether bank j_2 is directly connected with bank *i*. In other words, the systemic risk impact of an additional unit of connection is lower when a bank is already largely connected with other banks in the banking system.

The concept is not exclusive and is similar to that of local density in social network theory. In particular, local density measures the extent to which an agent's contacts have contacts among themselves. When density is high, the rate of information diffusion from an agent declines. (Granovetter, 1973, 1983; Yamaguchi, 1994).

2. Individual Bank Vulnerabilities

To test the hypothesis of whether herding affects systemic risk, the log transformation of the herding measures are interacted with individual bank vulnerabilities variables. Laeven, Ratnovski and Tong (2016) use several measures of individual bank vulnerabilities. The measures can be categorised in broad terms into: (a) capital structure; (b) funding structure; and (c) asset structure.

Capital Structure

Besanko and Kanatas (1996) argue that higher capital leads to effort-aversion moral hazard by diluting insiders' ownership. In particular, loans have positive net value, and rent is generated when loans are financed at a risk-insensitive price due to fixed deposits insurance premia. Requiring the bank to substitute equity for a given deposit financing, for a given set of assets, reduces the rent insiders receive. Hence, insiders have less incentive to monitor and collect the loans, increasing the default risk of the bank. The effect is consistent even when higher capital is expected to reduce the asset-substitution moral-hazard problem. The net effect of the two types of agency problem is an increase in the overall riskiness of bank assets.

However, Berger and Bowman (2013) point out two groups of hypotheses which argue that capital reduces banks' default risk. The first hypothesis emphasises the role of capital as a buffer to absorb shocks to earnings (Repullo, 2004). Another group emphasises the incentive effects of capital on bank risk, which includes theories based on screening, monitoring and asset-substitution moral hazard (Merton, 1977a; Coval and Thakor, 2005; Mehran and Thakor, 2011).

The screening-based theory argues banks exist because they can credibly pre-commit to screen optimistic entrepreneurs' projects. By offering pessimistic investors credible (riskless) debt contract, which is supported by the projects' payoffs and banks capital, banks are able to raise external capital for these projects. Hence, capital plays a critical role in assuring the viability of banks as financial intermediaries. Concerning the monitoring-based hypothesis, the theory suggests that higher capital increases the incentives for banks to monitor their debtors. In particular, higher capital increases banks' survival probabilities. This, in turn, increases banks' monitoring efforts, because a higher survival probability implies a higher likelihood of receiving the payoffs from the loans the banks monitor. Furthermore, the asset-substitution moral hazard theory argues capital reduces excessive risk-taking incentives induced by limited liability and deposit insurance. Thereby, banks with more capital optimally choose less risky portfolios.

The argument of Calem and Rob (1999) provides a middle ground for the two strands of literature. They propose that the effect of capital on individual bank risk differs conditional on ex-ante bank capital level. In particular, higher capital reduces moral hazard problems and risk-taking when banks are undercapitalised. However, for well-capitalised banks, higher capital induces them to take more risks. In particular, at a higher capital level, incremental investment in risky assets is related with smaller incremental risk of insolvency, as banks have a larger buffer to withstand losses. That said, the expected return of the risky assets is higher compared to that of the safe assets, providing incentives for banks to take higher risks.

Acharya, Mehran and Thakor (2016) also show that low capital induces asset-substitution moral hazard problem due to limited liability. Nonetheless, when the capital level is high, creditors lack incentives to impose discipline, as debt becomes so safe, inducing banks to take excessive risk. Several empirical findings have also suggested that the effects of capital on bank survival and systemic risk differs according to bank size (Berger and Bouwman, 2013; Laeven, Ratnovski and Tong, 2016).

This study hypothesises that systemic risk is inversely related to the interaction between herding and capital ratio. A lower capital ratio increases banks' incentive to take higher credit and market risk. The risks may spillover to other banks through various channels, as explained in section 3.3.2 of this chapter. Furthermore, when banks herd, these channels are reinforced, therefore, amplifying the effect of lower capital ratio on systemic risk. In addition, following Laeven *et al.* (2016), the interaction between capital ratio and bank size is included to capture the differences in the effect of capital due to differences in bank size.

Following several studies on bank leverage (Adrian and Shin, 2014; Laux and Rauter, 2017), capital ratio is measured by the ratio of book equity to total assets. Compared to the ratio of market equity, which is measured using enterprise value (debt + market equity), the ratio of book equity to total assets is more appropriate for capturing the procyclicality effect of capital ratio. In particular, the later ratio uses total assets, which is more related to the supply credit of banks. However, enterprise value is more related to how much a bank is worth. Data on both the ratio of book equity to total assets and total assets are obtained from Orbis Bank Focus.

Funding Structure

Calomiris (1999) discusses how subordinated debtholders can perform the function of monitoring a bank if such debt is not covered by a deposit insurance scheme. In such a condition, the use of debt in a bank's funding structure could reduce bank vulnerability through improved monitoring. In a related work, Diamond and Rajan (2001) show how short-term demandable deposits allow banks to commit to paying depositors' the full return of their loans. In particular, if a bank threatens to capture the rent from lending, the action will trigger a run by depositors, diminishing the value of the rent. Hence, a fragile funding structure which is subject to a bank run exerts discipline on the bank.

However, others have argued that wholesale funding exposes banks to funding risk. Wholesale funds, which are commonly short-term, increase banks' vulnerability to funding risk and liquidity risk because of the greater maturity mismatch between assets and liabilities. This, in turn, could lead to insolvency problem, as banks that rely excessively on short-term funding are more prone to assets fire-sales (Allen, Babus and Carletti, 2012; López-Espinosa *et al.*, 2012; Agur, 2014).

In addition, banks that depend on wholesale funding are exposed to information-based contagion. In particular, although wholesale financiers are more informed, they have imperfect information regarding the precise value of their bank's assets and receive noise on the assets portfolio. Thus, adverse information on the state of other banks that have common asset exposures with their banks influence wholesale financiers' beliefs regarding the state of their banks (Chen, 1999; Huang and Ratnovski, 2011).

Accordingly, this study hypothesises that systemic risk is inversely related to the interaction between herding and stable funding. Following Laeven, Ratnovski and Tong (2016), stable funding is measured by the ratio of customer deposits to total assets. Data on the variable are collected from Orbis Bank Focus.

Asset Structure

Banks whose asset portfolios are dominated by lending activity are more vulnerable to liquidity risk, because relationship-specific skills are required to collect the loans (Diamond and Rajan, 2001). These skills may be related to specific borrower information that a particular bank acquires through repeated interactions with the borrower or certain economic sectors. As other banks lack the skills to generate the full value of repayment from the borrower compared to the original bank, the loans will generate a lower liquidation value when sold to others.

The specialised human capital need not to be individual bank-specific but can also be industry-specific and still expose banks to liquidity risk. In particular, loans are transferable at a price that reflects their fundamentals when they are purchased by other banks endowed with the same degree of specialised human capital. Nonetheless, when purchased by outside investors, the loan is sold at a discount. Consequently, although the severity of the liquidity problem is low in tranquil times, banks are highly exposed to liquidity constraints during a financial crisis. During this period, a large portion of the banking sector is severely impaired, and the capacity for the industry to absorb outstanding loans is constrained. Accordingly, banks must liquidate some of their assets to outside investors and receive a lower liquidation value (Acharya and Yorulmazer, 2007).

In addition, the liquidity problem may also give rise to fire-sale externality when banks have common asset exposure (Cifuentes, Ferrucci and Shin, 2005). The adverse effect of forced liquidation on price may induce further asset liquidation, as it interacts with capital requirements and the risk management policy of other banks, causing a downward spiral in asset value.

Moreover, asset securitisation has been introduced to improve bank loans' transferability, and banks can use the technology to avoid lower liquidation value. Nonetheless, as evident from the global financial crisis, these assets are exposed to the same specialised human capital problem inherent in bank lending. Securitised loans are complex and difficult-to-value, exposing outside investors to valuation risk (Flannery, Kwan and Nimalendran, 2013).

Accordingly, this study hypothesises that systemic risk is positively related to the interaction between herding and bank exposure to illiquid assets. Following Laeven, Ratnovski and Tong (2016), the proportion of illiquid assets that a bank holds is measured by the ratio of loans to total assets. Data on the ratio of loans to total assets are obtained from Orbis Bank Focus.

3.5.4. Control Variables

As suggested by several studies, asset size may affect systemic risk (Adrian and Brunnermeier, 2016; Laeven, Ratnovski and Tong, 2016). In addition, Acharya and Yorulmazer (2007) suggest that small banks are likely to follow large banks, which the first empirical chapter ("Bank Herding and its Determinants") also finds some evidence for. Hence, to control for the spurious relationship between systemic risk and herding due to asset size, the latter variable is included in the regression. Data on bank total assets are acquired from Orbis Bank Focus.

Furthermore, De Bandt and Hartmann (2000) argue that studies related to systemic risk must control for the presence of financial safety nets in many countries to account for the effect of the factor on bank contagion. These provisions, which include deposit insurance schemes and lender-of-last-resort facilities, are set-up to mitigate the effect of individual bank failures spilling over to the rest of the banking system. The inclusion of these variables also controls for the spurious relationship between systemic risk and herding due to government support. Following Laeven, Ratnovski and Tong (2016), the interaction between bank size and both the availability of an explicit deposit insurance scheme and natural logarithm real GDP per capita are included in the regression.

The interaction between a bank's log total assets and a deposit insurance scheme is used to capture the implicit support for large banks. The impact of deposit insurance could go one of two ways. On the one hand, it may reduce the probability of bank panics and, hence, systemic risk. On the other hand, underpriced deposit insurance may induce moral hazard, increasing systemic risk. A deposit insurance scheme is defined as the presence of an explicit deposit insurance scheme within a country. A dummy variable is created and set equal to 1 if a country has explicit deposit insurance and set to 0 otherwise. Explicit deposit insurance scheme data are collected from the World Bank Deposit Insurance database. The database is published in 2015 with data dated as of end 2013.

Following Laeven, Ratnovski and Tong (2016), the government's ability to support a distressed banking system is measured by the interaction between banks' log total assets and log GDP per capita. Moreover, the effect of the variable on systemic risk is conditional on the systemic risk measure. More precisely, the signal of government support may increase the expectation of bailouts during a crisis, which induces banks to take a higher risk due to limited liability (Merton, 1977a). Consequently, banks are more vulnerable to common macroeconomic risk or systematic shocks, measured by SRISK. However, the expectation of government support during a crisis may reduce spillover risk (Laeven, Ratnovski and Tong, 2016; Dell'Ariccia and Ratnovski, 2019), mitigating the effect on ΔCoVaR. Data on real GDP per capita are collected from the International Monetary Fund World Economic Outlook as of October 2018.

In addition to country-specific financial safety nets, De Bandt and Hartmann (2000) argue that macroeconomic factors should be controled for in studies related to systemic risk. The inclusion of these factors is intended to separate bank contagion, which is the interest of this research, from joint bank failures as a consequence of macroeconomic shock. Accordingly, real GDP growth and inflation rate are included in the regression.

This study hypothesises that systemic risk is inversely related to macroeconomic conditions. Adverse macroeconomic conditions, indicated by a negative or low real

GDP growth and declining asset prices, may weaken bank condition and increase systemic risk (De Bandt and Hartmann, 2000). Nonetheless, concerning inflation rate, the relationship between the factor and systemic risk could also be positive. Higher asset prices may induce lending booms and spurious herding (Uchida and Nakagawa, 2007), which is associated with wider business cycle fluctuation and a higher likelihood of systemic risk. Data on both macroeconomic variables are collected from the International Monetary Fund World Economic Outlook Database as of October 2018.

3.5.5. Summary Statistics

Table 3.1 shows some evidence of correlation between the bank-level herding measures and bank size. More precisely, the correlations between bank size, *Log Total Assets*, and both *DGC Leader* and *DGC Follower* are each 0.059 and -0.006, each significant at the 1% level. This suggests that the number of banks that follow a particular bank increases with the size of the lead bank, and that the smaller banks are more likely to follow others. Therefore, confirming Acharya and Yorulmazer (2007).

The initial result also suggests consistency between the bank-level measure and the findings in the first empirical chapter ("Bank Herding and its Determinants"). More precisely, one of the main findings of the first empirical chapter is that herding is more prevalent in countries where the size difference between large and small banks is large.

Table 3.2 shows the summary statistics of the systemic risk measures and measures of individual bank vulnerabilities used in the regression analysis in this chapter. Following Laeven, Ratnovski and Tong (2016), both systemic risk measures Δ*CoVaR* and *Log SRISK* are winsorised at the top and bottom 1% level. Furthermore, consistent with the treatment for the country-level DGC measures in the first empirical chapter ("Bank Herding and its Determinants"), the interactions between the bank-level DGC measures and individual bank vulnerabilities are also winsorised at the same level to reduce the influence of potential outliers due to estimation error.

The summary statistics show that Δ*CoVaR* ranges from a low of -0.134% to a high of 5.489%. A positive sign of 5.849% indicates that the distress of a specific individual bank would lead to a 5.849% decline in the overall banking system equity. Consequently, a negative sign may indicate that the distress of a specific individual bank would lead to acquisition within the industry, generating surplus from higher efficiency. In addition, *Log SRISK* ranges from a low of -2.097 to a high of 10.475. This is equivalent to a capital shortfall of between USD 0.12 million and USD 35,415.97 million due to a systematic shock.

Table 3.3 reports the pairwise correlations between the systemic risk measures, individual bank vulnerabilities and the interactions between herding and individual bank vulnerabilities. The table shows a correlation of 0.510 between Δ*CoVaR* and *Log SRISK*, suggesting that each measure captures different aspects of systemic risk. Laeven, Ratnovski and Tong (2016) find a correlation of 0.43 between the two measures.

The correlation of the systemic risk measures with individual bank vulnerabilities and with the interaction terms are generally significant. In addition, the directions of the correlations between the systemic risk measures and the interaction terms are mostly consistent with those between the systemic risk measures and the related individual bank vulnerabilities. This suggests that the herding measures influence the magnitude but not the direction of the correlations between the systemic risk measures and individual bank vulnerabilities.

In addition, the correlation of the systemic risk measures with *Log Total Assets* are both positive at the 1% significance level. This suggests that the distress of larger banks leads to higher systemic risk. The positive correlation of $\Delta CoVaR$ with bank size is also consistent with our analysis related to Table 3.2. In particular, the failure of larger banks would cause a systemic loss in the banking system. However, the failure of smaller banks may instead lead to acquisition efficiency.

3.6. Results

The key objective of this research is to examine the systemic risk implications of bank herding. Recent theoretical work has shown that bank interconnectedness can increase systemic risk through different channels of financial contagion. Furthermore, several studies have argued that systemic risk taking, i.e. through herding, reinforces the propagation channels of systemic risk.

Therefore, to test the hypotheses on the effect of herding on systemic risk, the interactions between herding and individual bank vulnerabilities are used in the regression. Individual bank vulnerabilities in this study includes: capital structure; funding structure and bank asset structure. Furthermore, systemic risk is measured by $\Delta CoVaR$ and the logarithm transformation of SRISK, *Log SRISK*.

As explained in section 3.3.5 of this chapter, studies related to systemic risk measurement do not commonly identify the propagation channels explicitly (Benoit *et al.*, 2017). These studies tend to focus more on identifying key individual bank vulnerabilities that determine systemic risk. In addition, De Bandt and Hartmann

(2000) argue that studies related to systemic risk need to control for the presence of financial safety nets in many countries to account for the effect of the factor on bank contagion. Furthermore, they highlight the importance of including marcroeconomic factors to separate bank contagion from joint bank failures as a consequence of macroeconomic shock.

Accordingly, estimates of six testable models are presented in Table 3.4 to examine how the inclusion of the different factors affects systemic risk analyses. More precisely, column (1) presents the results when only individual bank vulnerabilities and other bank-specific characteristics are used to explain systemic risk, measured by Δ*CoVaR*. Next, column (2) reports the results when the model is extended to include both bank-specific characteristics and the interactions between herding and individual bank vulnerabilities, as a form of bank interconnectedness. Finally, column (3) shows the results when financial safety nets and macroeconomic factors are also included in the model. The same steps apply to the models presented in columns (4)–(6), which uses *Log SRISK* as the dependent variable.

Table 3.4 column (1) shows that systemic risk is associated with individual bank vulnerabilities. *Equity/Total Assets* is inversely related with Δ*CoVaR* and statistically significant at the 10% level, suggesting that well-capitalised banks pose less systemic risk. This result is consistent with other studies which have argued that capital reduces the probability of bank defaults and systemic risk (Merton, 1977a; Coval and Thakor, 2005; Mehran and Thakor, 2011). *Deposits/Total Assets* is also inversely related with Δ*CoVaR* and statistically significant at the 10% level. This finding is consistent with earlier studies that have argued that short-term funding increases banks' vulnerability to funding risk (Allen, Babus and Carletti, 2012; López-Espinosa *et al.*, 2012; Agur, 2014). *Loans/Total Assets*, which measures banks' exposure to illiquid assets, is positively related with $\Delta CoVaR$ and statistically significant at the 5% level. This finding is consistent with other studies which have suggested that loans expose banks to liquidity risk. More precisely, banks in which lending activity dominates their assets portfolio are more vulnerable to liquidity risk, because relationship-specific skills are required to collect the loans (Diamond and Rajan, 2001; Diamond and Rajan, 2005).

Table 3.4 column (2) shows that most of the interactions between individual bank vulnerabilities and herding are statistically significant in explaining systemic risk variation across banks. The finding highlights the importance of accounting for bank interconnectedness in systemic risk analyses. The interaction between herding and bank funding structure (*Deposits x LogLeader*) and that between herding and bank assets structure (*Loans x LogLeader*) are both statistically significant at the 1% and 5% levels. However, the interaction between herding and bank capital structure (*Equity x LogLeader*) is not. This suggests that Basel III, which imposes higher capital for designated systemically important banks, may have reduced to some extent the systemic risk implications of bank herding.

The introduction of the Basel III regulation may deter larger banks from taking excessive credit and market risks and, thereby, reduce the negative externalities from too-big-to-fail.[15] In addition, the regulation may also deter smaller banks from herding. In particular, as Basel III is expected to reduce government support for too-big-to-fail banks (Bongini, Nieri and Pelagatti, 2015; Moenninghoff, Ongena and Wieandt,

[15] Several studies find that global systemically important banks (G-SIBs) and many large banks have moved away from trading and more complex activities; hence, reducing market risk from the pre-crisis level. The average risk weight on banks' assets has also declined, reflecting a shift in the composition of credit portfolios towards assets with lower risk weights (BIS, 2018; Caparusso *et al.*, 2019).

2015), smaller banks may have less incentive to follow larger banks, therefore reducing commonality in credit and market risk exposure across banks.[16]

However, negative externalities from excessive funding risk and liquidity risk taking may have not been fully internalised through existing regulations. In particular, although Basel III regulations require banks to hold a liquidity buffer and impose a limit on maturity mismatch, the liquidity standards focus more on mitigating individual bank vulnerabilities. Consequently, banks may hold excessive illiquid assets and have less stable funding relative to the socially optimal level and increase their interconnectedness due to government bailout expectations when they collectively fail (Farhi and Tirole, 2012). Hence, when these banks become distressed, the effect of fire-sales on asset prices and contagion is greater.[17] Accordingly, this study suggests that there is still room for regulatory improvements by relating the liquidity standards with the cross-sectional dimension of systemic risk. The results support the argument of Acharya (2009) that regulatory mechanisms should be contingent on the risks correlation across banks

In addition, most of the interactions between individual bank vulnerabilities and the natural logarithm of the DGC Leader measure (*LogLeader*) are statistically significant. Nonetheless, the interactions with DGC Follower measure (*LogFollower*) are not. This result suggests that an idiosyncratic shock or the distress of a bank which is followed by other banks poses a contagion risk. This is consistent with other studies which are proponents of the information-based contagion hypothesis (Aharony and

[16] As discussed in section 3.3.2 of this chapter, several studies have suggested that common asset exposures among banks can lead to systemic risk (Lehar, 2005; Ibragimov, Jaffee and Walden, 2011; Cai *et al.*, 2018).

[17] Alternatively, to meet liquidity demand, these banks may have to borrow from the market at a fire-sale premium due to information-based contagion, therefore reducing their intrinsic value.

Swary, 1996; Chen, 1999). However, it does add to the findings of earlier research by showing that the market identifies which banks are more likely to trigger a contagion effect among those banks which have similar financial characteristics.

Table 3.4 column (3) shows that the statistical significance of the interaction terms is consistent after controlling for financial safety nets and country-specific macroeconomic factors. The column also illustrates that the coefficient of bank size (*Log Total Assets*) is positive and statistically significant at the 1% level. The finding is consistent with earlier empirical research which suggests that systemic risk is positively related to bank size (Adrian and Brunnermeier, 2016; Laeven, Ratnovski and Tong, 2016). In addition, the result demonstrates that the coefficient of the interaction between log GDP per capita and log total assets (*LogGDP x LogTotalAssets*) is negative and statistically significant at the 1% level. This suggests that the expectations of government support for banks during a crisis reduces contagion risk (Laeven, Ratnovski and Tong, 2016; Dell'Ariccia and Ratnovski, 2019).

Table 3.4 columns (4)–(6) reports the relationship between *Log SRISK* and its determinants. The coefficients of bank size (*Log Total Assets*) are positive and statistically significant at the 1% level in columns (4) and (5) and 5% in column (6). The finding is consistent with earlier empirical research that finds that size affects systemic risk (Adrian and Brunnermeier, 2016; Laeven, Ratnovski and Tong, 2016).

Table 3.4 column (5) shows that *Deposits/Total Assets* is negatively related to capital shortfall and significant at the 10% level, suggesting short-term funding increases banks' vulnerabilities to systematic shocks. Furthermore, *Loans/Total Assets* is positively related to *Log SRISK* and significant at 5%, indicating that exposure to illiquid assets increases bank vulnerabilities. The significance level of both variables also improves after the inclusion of financial safety nets and macroeconomic factors in column (6).

Moreover, consistent with the Δ*CoVaR* model in column (3), *Deposit x LogLeader* and *Loans x LogLeader* are both statistically significant each at 5% and 10% levels in column (6). Nonetheless, unlike the Δ*CoVaR* model, *Log SRISK* is positively related to *Deposit x LogLeader* and inversely related to *Loans x LogLeader*. Analysing the interaction terms jointly with the related individual bank vulnerabilities suggests that banks with higher vulnerabilities, measured by higher (lower) *Loans/Total Assets* (*Deposits/Total Assets*), are more fragile to systematic shocks. Nonetheless, herding reduces the effect of the shocks on capital shortfall, as measured by *Log SRISK*. Furthermore, when banks reduce their vulnerabilities, as measured by lower (higher) *Loans/Total Assets* (*Deposits/Total Assets*), banks that herd experience a smaller decline in their capital shortfall (*Log SRISK*).

This result suggests that *Log SRISK* captures the market expectations of bailout subsidies. In particular, when banks increase their vulnerabilities to systematic shocks, the market expects higher likelihood of collective failure and government bailouts for banks that herd. Accordingly, the amount of capital shortfall (*Log SRISK*) for these banks is lower when banks vulnerabilities increase. However, when banks reduce their vulnerabilities to systematic shocks, expectations of government bailout also decline. Hence, the decline in capital shortfall (*Log SRISK*) due to lower vulnerabilities is offset by lower gains from the reduced expectations of government subsidies.

The finding is consistent with the argument of Laeven, Ratnovski and Tong (2016) that market values of bank equity may reflect the market expectations of government support. This further supports the theories on herding (Acharya and Yorulmazer, 2007;

Farhi and Tirole, 2012) and the findings of the first empirical chapter ("Bank Herding and its Determinants"), which suggests that the likelihood of bailout subsidies induces herding.

Moreover, Table 3.4 column (6) shows that the coefficient of the interaction between log GDP per capita and log total assets (*LogGDP x LogTotalAssets*) is positive and significant at the 10% level. This result contradicts that of the $\Delta CoVaR$ model in column (3). This suggests that the expectations of government support during a crisis reduce spillover risk, measured by $\Delta CoVaR$ (Laeven, Ratnovski and Tong, 2016; Dell'Ariccia and Ratnovski, 2019). However, when banks expect to be bailed out in a crisis, they may take higher risks due to limited liability (Merton, 1977a), therefore increasing their vulnerabilities to systematic shocks.

Furthermore, the coefficient of the interaction term of deposit insurance and log total assets (*DepInsurance x LogTotalAssets*) is negative and statistically significant at the 1% level. This indicates that the presence of deposit insurance reduces the occurrence of bank panics, which are often associated with adverse macroeconomic shocks (Levy-Yeyati, Martínez Pería and Schmukler, 2010). The conflicting findings between the financial safety net measures are consistent with Goodhart and Huang (2005). They argue that financial safety nets induce a moral hazard problem and risk-taking behaviour but limit the spillover effects which usually occur in a financial crisis. In addition, the result in Table 3.4 column (6) shows that lower real GDP growth, which is associated with adverse macroeconomic conditions, may weaken financial institutions and increase systemic risk (De Bandt and Hartmann, 2000).

3.7. Robustness Checks

3.7.1. Alternative Measure of Capital Ratio

In this study, book equity to total assets is used to measure capital ratio. The approach is slightly different compared to Laeven, Ratnovski and Tong (2016), who uses tier 1 capital to total risk-weighted assets. They argue that tier 1 capital ratio, by controlling both for the riskiness of assets and the quality of capital, is a more accurate measure of bank capital compared to leverage ratio.

Nonetheless, the correlation between the book leverage ratio and *Tier 1 ratio* is relatively strong at 0.74 with a significance level of 5%, suggesting that the use of either measure is likely to generate similar results. In addition, the equity to total assets ratio captures a larger set of sample compared to the latter. In particular, data on the ratio are available for 3,501 bank-year observation and those on tier 1 capital ratio covers 2,312 bank-year observation. Hence, a larger sample size is preferred to improve the efficiency of the parameter estimates.

To further examine the sensitivity of the model to different measures of capital ratio, *Tier 1 ratio* is used as an alternative to the book leverage ratio. Data on *Tier 1 ratio* are obtained from Orbis Bank Focus. The estimation result, using Tier 1 ratio as the measure for capital ratio, is presented in Table 3.5.

The table suggests that the estimation result for the interaction terms is relatively consistent, using different measures of capital ratio. In addition, inflation rate (*Inflation*), which is one of the macroeconomic variables, shows a conflicting sign between the Δ*CoVaR* model in column (3) and the *Log SRISK* model in column (6). This is because each systemic risk measure captures a different aspect of systemic risk. In particular, Δ*CoVaR* measures the contagion effect of the distress of an individual bank on the rest of the banking system. However, *SRISK* measures individual bank vulnerabilities to systematic shocks. Hence, in the $\Delta CoVaR$ model, higher asset prices – as measured by a higher inflation rate – induce lending booms and contagion risk from spurious herding (Uchida and Nakagawa, 2007). Therefore, increasing interconnectedness among banks due to a simultaneous response to favourable macroeconomic conditions. However, in the SRISK model, declining asset prices is associated with adverse macroeconomic conditions which may weaken financial institutions and increase systemic risk (De Bandt and Hartmann, 2000).

3.7.2. Testing for Functional Form Misspecification

As explained in section 3.5.3 of this chapter, the use of the natural logarithm form of the herding measures (log DGC measures) in this study provides an intuitive economic interpretation on the relationship between herding and systemic risk. Nonetheless, the transformation of the herding measures may introduce an endogeneity problem when the model is misspecified.

Accordingly, to test whether the logarithm transformation of the herding measures provides a better estimate of systemic risk, the Davidson–Mackinnon J test for nonnested models is considered (Greene, 2017). The test uses the same approach applied in the Ramsey's RESET test for nested models. In particular, let

$$H_0: y_{i,t} = \beta_1 x_{1,i,t-1} + \sum_{k=3}^{K} \beta_k \, x_{k,i,t-1} + \mu_i + \lambda_t + v_{1,i,t} \tag{3.32}$$

$$H_a: y_{i,t} = \beta_2 x_{2,i,,t-1} + \sum_{k=3}^{K} \beta_k \, x_{k,i,t-1} + \mu_i + \lambda_t + v_{2,i,t} \tag{3.33}$$

Where $y_{i,t}$ denotes systemic risk, measured by $\Delta CoVaR$; $x_{1,i,t-1}$, $x_{2,i,t-1}$ and $x_{k,i,t-1}$ are respectively the first lag of: the interactions between individual bank vulnerabilities and DGC measures without the log transformation, the interactions between individual bank vulnerabilities and log DGC measures, and other time-variant explanatory variables; μ_i is the time-invariant unobserved bank heterogeneity; λ_t is the unobserved time effects; and $v_{i,t}$ is the idiosyncratic component.

The J test is performed by generating the predicted values $\hat{y}_0$ and $\hat{y}_a$of equation (3.32) and (3.33) respectively and including them in the augmented regression of the other equation. More specifically, $\hat{y}_a$ is included in equation (3.32) to test the null hypothesis that equation (3.32) is correctly specified and the inclusion of log DGC measures has no power to improve it. If the coefficient estimate for $\hat{y}_a$ is significant, the null hypothesis is rejected. Similarly, to test equation (3.33), $\hat{y}_0$ is included in equation (3.33) and the null hypothesis that equation (3.33) is correctly specified is rejected if the coefficient estimate for $\hat{y}_0$ is significant. Table 3.6 shows the result of the test in which equation (3.33) dominates equation (3.32), suggesting that the natural logarithm form of the herding measures is preferable.

3.8. Conclusions

The objective of this study was to investigate whether herding, as observed in the previous empirical chapter ("Bank Herding and its Determinants"), poses a systemic risk. Systemic risk is measured using both ΔCoVaR (Adrian and Brunnermeier, 2016) and SRISK (Brownlees and Engle, 2017). In addition, herding is measured by bank-level degree of Granger causality. Following Laeven, Ratnovski and Tong (2016), individual bank vulnerabilities are measured by: (a) equity to total assets; (b) deposits to total assets and (c) loans to total assets respectively.

The systemic measures are then regressed on the interactions between individual bank vulnerabilities and the herding measures, controlling for bank-specific characteristics, financial safety nets and country-specific macroeconomic factors. In addition, bank fixed effects and year fixed effects are included to control for time-invariant unobserved bank heterogeneity and unobserved time effects. Within transformation and truncated regression are used to estimate the parameters.

The empirical results show that herding influences systemic risk through its interactions with individual bank vulnerabilities. This suggests that the behaviour amplifies the effect of individual bank vulnerabilities on systemic risk by reinforcing the propagation channels of the risk. In addition, the market may have expectations of bailout subsidies should banks collectively default. This is indicated by the lower estimated capital shortfall under a severe systematic shock, SRISK, for banks that herd. The findings are consistent with the theory that the likelihood of government bailouts induces herding (Acharya and Yorulmazer, 2007; Farhi and Tirole, 2012).

In addition, the results indicate that an idiosyncratic shock or the distress of a bank, which is followed by other banks, poses contagion risk. This is consistent with other studies that support the information-based contagion hypothesis. In addition, the results refine those of earlier studies. In particular, the findings suggest that the market distinguishes which banks are more likely to trigger spillover effects among those banks with common financial characteristics.

Next, the empirical results reveal that most of the interactions between individual bank vulnerabilities and herding are statistically significant in explaining systemic risk variation across banks. The finding highlights the importance of accounting for bank interconnectedness to improve systemic risk analyses and related policy recommendations.

Finally, compared to the interactions between herding and bank funding structure and assets structure, those between herding and bank capital structure are not statistically significant. This suggests that the current regulation, which links minimum capital ratio requirements with the systemic importance of a bank, may have reduced the systemic risk implications of herding. However, negative externalities from excessive funding risk and liquidity risk taking may have not been fully internalized through existing regulations. Accordingly, the study suggests that there is still room for regulatory improvements by relating the liquidity standards with the cross-sectional dimension of systemic risk. The result also supports the argument of Acharya (2009) that regulatory mechanisms should be contingent on the risk correlation across banks.

Table 3.1

Pairwise correlations between bank size and the herding measures

In parentheses and brackets below the correlation are the corresponding p-values and the number of observations, respectively. Log Total Assets is the natural logarithm of bank total assets, measured in thousands of USD. DGC Leader and DGC Follower are the herding measures. The former (latter) measure captures the extent of herding or mimicking of bank i (other banks j) by other banks j (bank i), or bank i acting as leader (follower) in the herd, as the fraction of statistically significant $\beta_{j,i}$ ($\beta_{i,j}$), according to the one-way Granger causality test, among N-1 number of banks within a country.

	Log Total Assets	DGC Leader	DGC Follower
Log Total Assets	1		
	[3,501]		
DGC Leader	0.0586	1	
	(0.0034)		
	[2,499]	[2,686]	
DGC Follower	-0.0062	-0.1740	1
	(0.0001)	(0.0000)	
	[2,499]	[2,686]	[2,686]

Table 3.2
Summary statistics

This table provides the summary statistics of the main regression variables. ΔCoVaR (%) is the ΔCoVaR, expressed in percentages. Log SRISK is the natural logarithm of SRISK, which is measured in millions of USD and following Brownlees and Engle (2017), is limited from positive value to zero. Both ΔCoVaR and Log SRISK are computed for 2013–2017 using recursive sampling from January 2000 to include the 2008 Global Financial Crisis. Log DGC-Leader and Log DGC-Follower are both the natural logarithm of the herding measures. Equity/Total Assets (%) is the ratio equity to total assets. Loans/Total Assets (%) is the ratio of net loans to total assets. Deposits/Total Assets (%) is the ratio of deposits to total assets. Variables related to bank vulnerabilities are all expressed in percentages. Log Total Assets is the natural logarithm of total assets (in thousands of USD). Deposit Insurance is a dummy variable equal to one when there is an explicit deposit insurance scheme. Log GDP per capita is the natural logarithm of GDP per capita. GDP Growth (%) and Inflation (%) are each country-specific GDP growth and inflation rate, expressed in percentages. All explanatory variables are lagged by one year.

Variable	N	Min.	Q1	Mean	Median	Q3	Max	Std. Dev.
Dependent Variable								
ΔCoVaR (%)	2,804	-0.134	0.653	1.944	1.856	2.990	5.489	1.417
Log SRISK	1,421	-2.097	3.445	5.121	5.575	6.809	10.475	2.438
Herding Measures								
Log DGC-Leader	1,778	0.3711	1.802	2.340	2.332	2.996	4.317	0.819
Log DGC-Follower	1,769	0.3711	1.772	2.342	2.332	2.936	4.465	0.838
Bank Vulnerabilities								
Equity/Total Assets (%)	3,501	-175.919	6.571	10.325	9.249	12.447	83.956	7.532
Deposits/Total Assets (%)	3,501	0.374	62.387	70.569	74.200	82.354	256.118	16.455
Loans/Total Assets (%)	3,501	0.409	50.795	58.418	60.968	68.159	92.411	14.750
Log Total Assets	3,501	9.158	14.606	16.063	16.158	17.510	21.968	2.165
Financial Safety Nets								
Deposit Insurance	3,832	0.000	1.000	0.835	1.000	1.000	1.000	0.371
Log GDP per capita	3,723	6.014	8.212	9.398	9.514	10.609	11.702	1.330
Macroeconomic Factors								
GDP Growth (%)	3,832	-16.456	1.495	3.164	2.829	5.033	25.007	2.732
Inflation (%)	3,832	-3.402	0.602	3.562	2.066	4.916	302.637	10.316

Table 3.3
Pairwise correlations

This table reports pairwise correlations between systemic risk measures, individual bank vulnerabilities and the interactions between herding measures and individual bank vulnerabilities. In parentheses and brackets below the correlation are the corresponding p-values and the number of observations, respectively.

	ΔCoVaR (%)	Log SRISK	Equity/Total Assets (%)	Deposits/Total Assets (%)	Loans/Total Assets (%)	Log Total Assets	Equity x Log Leader	Equity x Log Follower	Deposits x Log Leader	Deposits x Log Follower	Loans x Log Leader	Loans x Log Follower
ΔCoVaR (%)	1											
	[2804]											
Log SRISK	0.5100	1										
	(0.0000)											
	[1154]	[1421]										
Equity/Total Assets (%)	-0.1585	-0.3718	1									
	(0.0000)	(0.0000)										
	[2609]	[1387]	[3501]									
Deposits/Total Assets (%)	-0.1158	0.0488	-0.3391	1								
	(0.0000)	(0.0693)	(0.0000)									
	[2609]	[1387]	[3501]	[3501]								
Loans/Total Assets (%)	-0.1403	-0.1291	-0.1724	0.2166	1							
	(0.0000)	(0.0000)	(0.0000)	(0.0000)								
	[2609]	[1387]	[3501]	[3501]	[3501]							
Log Total Assets	0.6133	0.6880	-0.3358	-0.2397	-0.0423	1						
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0123)							
	[2609]	[1387]	[3501]	[3501]	[3501]	[3501]						
Equity x Log Leader	-0.1292	-0.2481	0.7724	-0.4264	-0.1618	-0.2047	1					
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)						
	[1505]	[745]	[1654]	[1654]	[1654]	[1654]	[1654]					
Equity x Log Follower	-0.1788	-0.3143	0.7849	-0.3967	-0.0907	-0.2792	0.7591	1				
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0000)	(0.0000)					
	[1460]	[759]	[1638]	[1638]	[1638]	[1638]	[1149]	[1638]				
Deposits x Log Leader	-0.0612	-0.0413	-0.0445	0.2569	0.0532	-0.0472	0.4072	0.0377	1			
	(0.0176)	(0.2604)	(0.0705)	(0.0000)	(0.0306)	(0.0548)	(0.0000)	(0.2012)				
	[1505]	[745]	[1654]	[1654]	[1654]	[1654]	[1654]	[1149]	[1654]			
Deposits x Log Follower	-0.1230	-0.1416	-0.0201	0.2707	0.0729	-0.1473	0.0380	0.4220	0.1597	1		
	(0.0000)	(0.0001)	(0.4167)	(0.0000)	(0.0031)	(0.0000)	(0.1981)	(0.0000)	(0.0000)			
	[1460]	[759]	[1638]	[1638]	[1638]	[1638]	[1149]	[1638]	[1149]	[1638]		
Loans x Log Leader	-0.0467	-0.1561	0.0275	-0.1203	0.4962	0.0327	0.4563	0.1498	0.7324	0.0547	1	
	(0.0703)	(0.0000)	(0.2633)	(0.0000)	(0.0000)	(0.1836)	(0.0000)	(0.0000)	(0.0000)	(0.0639)		
	[1505]	[745]	[1654]	[1654]	[1654]	[1654]	[1654]	[1149]	[1654]	[1149]	[1654]	
Loans x Log Follower	-0.1348	-0.2264	0.0822	-0.1253	0.5041	-0.0655	0.1593	0.5017	0.0618	0.7503	0.3561	1
	(0.0000)	(0.0000)	(0.0009)	(0.0000)	(0.0000)	(0.0081)	(0.0000)	(0.0000)	(0.0362)	(0.0000)	(0.0000)	
	[1460]	[759]	[1638]	[1638]	[1638]	[1638]	[1149]	[1638]	[1149]	[1638]	[1149]	[1638]

Table 3.4
Systemic risk and bank herding relationship

This table reports regressions of the systemic risk measures and the interactions between herding and individual bank vulnerabilities, controlling for bank-specific characteristics, financial safety nets and country-specific macroeconomic conditions. Bank fixed effects and year fixed effects are both included to control for time-invariant unobserved bank heterogeneity and unobserved time effects respectively. All explanatory variables are lagged by one year. Standard errors, reported between parentheses, are clustered at the country level. ***,** and * denote statistical significance at the 1%, 5% and 10% level respectively. Parameters for ΔCoVaR are estimated using within transformation, and those related to SRISK are estimated using truncated regression. The later estimation method is used to avoid problems related to external validity. Imposing the definition of SRISK on the sample and using the log function to narrow the range of the SRISK value excludes banks with negative to zero SRISK.

	ΔCoVaR			Log SRISK		
	(1)	(2)	(3)	(4)	(5)	(6)
Bank-Specific Characteristics						
Equity/Total Assets (%)	-0.027*	-0.040	0.019	0.067	-0.246	-0.292
	(0.015)	(0.063)	(0.057)	(0.063)	(0.251)	(0.243)
Equity x LogTotalAssets	0.002	0.002	-0.001	-0.004	0.015	0.016
	(0.001)	(0.005)	(0.004)	(0.004)	(0.016)	(0.014)
Deposits/Total Assets (%)	-0.005*	-0.007	-0.001	-0.004	-0.028*	-0.031**
	(0.003)	(0.007)	(0.006)	(0.005)	(0.014)	(0.014)
Loans/Total Assets (%)	0.005**	-0.003	0.000	0.010*	0.025**	0.034***
	(0.002)	(0.004)	(0.004)	(0.006)	(0.010)	(0.010)
Log Total Assets	-0.025	-0.113	1.469***	0.659***	0.999***	1.507**
	(0.093)	(0.256)	(0.447)	(0.178)	(0.293)	(0.720)
Interactions with Herding						
Equity x LogLeader		0.002	0.002		0.016	0.022
		(0.003)	(0.003)		(0.030)	(0.030)
Equity x LogFollower		-0.004	-0.003		0.016	0.017
		(0.003)	(0.003)		(0.011)	(0.012)
Deposits x LogLeader		-0.002***	-0.002**		0.006*	0.006**
		(0.001)	(0.001)		(0.003)	(0.003)
Deposits x LogFollower		0.000	-0.000		-0.001	-0.000
		(0.001)	(0.001)		(0.002)	(0.002)
Loans x LogLeader		0.002**	0.002*		-0.010	-0.010*
		(0.001)	(0.001)		(0.006)	(0.006)
Loans x LogFollower		0.001	0.001		0.000	-0.002
		(0.002)	(0.002)		(0.002)	(0.003)
Control Variables						
LogGDP x LogTotalAssets			-0.077***			0.045*
			(0.021)			(0.024)
DepInsurance x LogTotalAssets			-0.316			-1.328***
			(0.349)			(0.471)
GDP Growth (%)			0.021			-0.085**
			(0.024)			(0.036)
Inflation (%)			0.010			-0.027
			(0.010)			(0.024)
Number of observations	2,609	1,052	1,042	1,375	568	561
R_squared	0.146	0.145	0.264			
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 3.5
Alternative measure of capital ratio

This table reports the coefficient estimates of robustness tests using Tier 1 capital to total risk-weighted assets as a measure capital ratio, (replacing equity to total assets in Table 3.4). All explanatory variables are lagged by one year. Standard errors, reported between parentheses, are clustered at the country level. ***, ** and * denote statistical significance at the 1%, 5% and 10% level respectively.

	ΔCoVaR			Log SRISK		
	(1)	(2)	(3)	(4)	(5)	(6)
Bank-Specific Characteristics						
Tier 1 ratio (%)	0.023	0.047	0.039	0.086	0.005	-0.151
	(0.034)	(0.091)	(0.088)	(0.098)	(0.123)	(0.206)
Tier 1 x LogTotalAssets	-0.001	-0.002	-0.001	-0.006	0.008	0.015
	(0.002)	(0.006)	(0.006)	(0.006)	(0.010)	(0.012)
Deposits/Total Assets (%)	-0.002	-0.006	0.002	-0.008	-0.035***	-0.031**
	(0.003)	(0.009)	(0.007)	(0.007)	(0.010)	(0.012)
Loans/Total Assets (%)	0.006**	0.001	-0.0000	0.017	0.041**	0.060***
	(0.003)	(0.006)	(0.007)	(0.010)	(0.017)	(0.020)
Log Total Assets	0.132	0.243	1.483***	0.503***	1.210***	1.526
	(0.114)	(0.271)	(0.470)	(0.191)	(0.300)	(0.944)
Interactions with Herding						
Tier 1 x LogLeader		-0.0000	-0.001		-0.041*	-0.026
		(0.003)	(0.003)		(0.024)	(0.022)
Tier 1 x LogFollower		-0.004	-0.003		0.004	0.011
		(0.004)	(0.004)		(0.016)	(0.014)
Deposits x LogLeader		-0.004**	-0.003**		0.012**	0.010*
		(0.002)	(0.002)		(0.005)	(0.005)
Deposits x LogFollower		0.003	0.002		0.001	0.003
		(0.002)	(0.002)		(0.004)	(0.004)
Loans x LogLeader		0.004*	0.004*		-0.009	-0.008
		(0.002)	(0.002)		(0.006)	(0.006)
Loans x LogFollower		-0.002	-0.001		-0.002	-0.007
		(0.002)	(0.002)		(0.006)	(0.006)
Control Variables						
LogGDP x LogTotalAssets			-0.050*			0.023
			(0.025)			(0.049)
DepInsurance x LogTotalAssets			-0.411			-1.009
			(0.390)			(0.769)
GDP Growth (%)			0.002			-0.145**
			(0.028)			(0.058)
Inflation (%)			0.025**			-0.075**
			(0.009)			(0.036)
Number of observations	1758	643	634	775	254	247
R_squared	0.180	0.171	0.235			
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 3.6
Davidson – MacKinnon J test

This table reports the result of the Davidson–MacKinnon J test (Baum, 2006; Greene, 2017). The purpose of the test is to analyse whether the log transformation of the herding measures provides a better estimate of systemic risk. The first test reports the test result for the null hypothesis that equation (3.32), the model that uses the herding measures without log transformation, is correctly specified and the inclusion of log DGC measures has no power to improve it. The null hypothesis for the first test is rejected when the coefficient estimate for $\hat{y}_a$ is statistically significant. The second test reports the test result for the null hypothesis that equation (3.33), the model that uses log transformation, is correctly specificed. The null hypothesis for the second test is rejected if the coefficient estimate for $\hat{y}_0$ is statistically significant. Both tests show that equation (3.33) dominates equation (3.32), suggesting that the natural logarithm form of the herding measures is preferable. Bank fixed effects and year fixed effects are both included in the regressions to control for time-invariant unobserved bank heterogeneity and unobserved time effects respectively. Standard errors, reported between parentheses, are clustered at the country level. ***,**, and * denote statistical significance at the 1%, 5%, and 10% level respectively.

First Test		Second Test	
Bank Characteristics		*Bank Characteristics*	
Equity/Total Assets (%)	-0.003	Equity/Total Assets (%)	0.064
	(0.070)		(0.094)
Equity x LogTotalAssets	0.000	Equity x LogTotalAssets	-0.005
	(0.005)		(0.007)
Deposits/Total Assets (%)	0.000	Deposits/Total Assets (%)	0.008
	(0.008)		(0.013)
Loans/Total assets (%)	0.000	Loans/Total assets (%)	-0.011
	(0.005)		(0.018)
Log Total Assets	-0.571	Log Total Assets	0.491
	(0.913)		(1.643)
Interactions with Herding		*Interactions with Herding*	
Equity x Leader	0.000	Equity x LogLeader	0.003
	(0.000)		(0.004)
Equity x Follower	0.000	Equity x LogFollower	-0.004
	(0.000)		(0.004)
Deposits x Leader	0.000	Deposits x LogLeader	-0.002*
	(0.000)		(0.001)
Deposits x Follower	0.000	Deposits x LogFollower	-0.001
	(0.000)		(0.002)
Loans x Leader	0.000	Loans x LogLeader	0.002
	(0.000)		(0.001)
Loans x Follower	0.000	Loans x LogFollower	0.002
	(0.000)		(0.002)
Control Variables		*Control Variables*	
LogGDP x LogTotalAssets	0.031	LogGDP x LogTotalAssets	-0.025
	(0.053)		(0.081)
DepInsurance x LogTotalAssets	0.104	DepInsurance x LogTotalAssets	0.026
	(0.495)		(0.733)
GDPGrowth (%)	-0.009	GDPGrowth (%)	0.011
	(0.036)		(0.035)
Inflation (%)	-0.005	Inflation (%)	0.010
	(0.011)		(0.013)
Predicted values		*Predicted values*	
$\hat{y}_a$	1.403**	$\hat{y}_0$	1.538
	(0.540)		(2.158)

4. The Effect of Herding on the Competition and Profit of Banks

4.1. Introduction

Acharya and Yorulmazer (2007) theorise that banks herd to increase the likelihood of a collective bailout position should default occur. However, their model does not account for the possible adverse effect of herding on profit as banks lend to similar economic sectors. Accordingly, profit deterioration could undermine herding incentives.

Uchida and Nakagawa (2007) find evidence of small regional banks in Japan herding between 1975–2000. There is also evidence of large city banks herding, but only during the asset-price bubble of the late 1980. Their findings suggest that small banks herd for a long period.[18] They also suggest that herding among the regional banks may be related to the lack of competition. In particular, competition among these banks was considered less intense compared to that among city banks in the Japanese loan market (Uchida and Tsutsui, 2005). This raises the empirical question of why herding remains desirable amidst the possibility of profit deterioration from herding.

Two possible reasons are proposed. First, competition among banks that herd is weaker compared to the rest of the banking industry (Uchida and Nakagawa, 2007). Banks that herd could operate in a less competitive banking market and/or are able to

[18] Barron and Valev (2000) find evidence of herding between a group of small U.S. banks and that of large U.S. banks in international lending during 1982–1994 (13 years). Jain and Gupta (1987), however, examine the same issue but using a different and shorter time period (1977–1982) and find weak evidence of herding between these two group of banks.

minimise the competition by colluding to protect themselves from profit deterioration. Banks that herd can collude and widen their profit margin by jointly increasing their lending rate and lowering their deposit rate. Therefore, maintaining profit while herding is feasible when the competition among the banks that herd is lower, possibly due to collusion. Although a direct test of whether banks collude is beyond the scope of this chapter, collusion is considered as a transmission mechanism through which herding can affect persistence in the profit of herding banks.[19]

Evidence of collusion among banks is well documented in the literature. For instance, Neven and Röller (1999) find evidence of collusive behaviour among banks in seven European nations between 1981–1989. Several banks in Korea were suspected of collusion in setting deposit rates and fees related to other services in 2006.[20] A number of international banks were also under investigation for suspected collusion in LIBOR and the manipulation of a multi-trillion-dollar government-backed bond market (Prasad, 2011; Kowsmann and Margot, 2018). Such banks include, among others, Bank of America, Citigroup and UBS. Moreover, the Reserve Bank of India in mid-2017 issued a new code of conduct in the foreign exchange market and bond market (Ghosh, 2017). The new code was introduced in response to the collusive behaviour of large-state owned banks in the local government securities market in India.

However, herding does not necessarily involve collusion. Collusion refers to a coordinated decision, such as pricing, aimed at preventing severe competition (Chang,

---

[19] Several empirical papers on bank competition and profit have also examined the presence of collusion using indirect measures of bank competition, such as market concentration (Smirlock, 1985; Goldberg and Rai, 1996; Mirzaei, Moore and Liu, 2013). They argue that a small number of banks in a concentrated market may be able to collude or exploit their market power independently.
[20] *Vietnam Investment Review* (2006) 'RoK probe into bank collusion.', 12 June, pp. 23.

1991) and, therefore, involves a feedback mechanism among the agents. Herding, however, involves the mimicking of an agent's behaviour by another agent (Bikhchandani and Sharma, 2000) and, therefore, does not require such a feedback mechanism to occur. Acharya and Yorulmazer (2007) also posit that in an asymmetric banking system, small banks follow larger banks and the latter instead prefer to differentiate themselves from the former.

A second possible reason for banks to engage in herding, amidst the possibility of reduced profit, is lower competition in the banking industry. According to this view, herding may increase competition and reduce profit when banks herd by providing loans to the same industries (Acharya and Yorulmazer, 2007). However, herding may still be desirable because weaker industry competition allows banks to generate excess profit and compensate for profit erosion caused by herding (Acharya and Yorulmazer, 2008).

Several studies have argued that the low level of competition may be related to government prioritisation of stability over competition during the 2008 Global Financial Crisis (Chronopoulos *et al.*, 2015; McMillan and McMillan, 2016). More precisely, government support of the largest banks to limit spillover effects increases bank concentration and reduces competition. Spokeviciute, Keasey and Vallascas (2019) also provide evidence that banks' efficiency following the global financial crisis has remained significantly lower compared to the pre-crisis level, suggesting evidence of reduced competition in the banking sector.

An empirical analysis on the effect of herding on the competition and profit of banks may provide some insights on the possibility of using competition policy as an alternative to prudential policy to mitigate systemic risk. The Basel Comittee on

Banking Supervision (2010) estimates that the capital and liquidity brought about by Basel III can have an impact on economic activity. Accordingly, examining the possibility of alternative approaches to mitigating systemic risk would be valuable. Conditional on the findings, regulators could impose fines on banks that herd to deter herding and mitigate systemic risk when herding involves collusion. They could also increase competition in the banking industry, with the result that banks have less of a buffer to withstand worsening profit from herding.

This chapter uses POP models to examine the effect of herding on the competition and profit of banks. Proponents of the POP models posit that competition eliminates excess profit and profits converge towards their long-run equilibrium. However, when competition is low, high profits can persist for a longer period and converge slowly to their long-run equilibrium (Mueller, 1977). The rate at which competition affects excess profit in the short-run is measured by the degree of first-order autocorrelation in time series profit.

Accordingly, when competition among banks that herd is weaker, the persistence in their profit is higher than that of the industry. This means the rate at which profits in the short-run converge towards their long-run equilibrium is minimised. However, when herding increases competition, the degree of persistence in their profit is lower. This means any excess profit in the short-run is eliminated quickly and the rate at which profits converge to their long-run equilibrium increases. Furthermore, profit persistence for banks in general is expected to be high or above 0.5 when competition in the banking industry is weak.

The results show evidence of a higher level of competition among the banks that herd compared to the rest of the industry. Profit is found to be inversely related to the degree of profit persistence conditional on herding. Nonetheless, herding is still desirable because competition in the banking industry is low. Furthermore, the results show that the adverse effect of increased competition on profit is higher for banks which are followed by other banks.

The findings reported above hold when U.S. and Western Europe countries are excluded from the analysis. The consistency between the sub-sample results and the full sample indicates that lower level of competition in banking industry seems to also be prevalent in other economies. Structural break tests are also employed to examine whether the results are consistent with prior studies that have suggested banking competition is lower following the 2008 financial crisis (Chronopoulos, Liu, McMillan and Wilson, 2015; McMillan and McMillan, 2016). The findings indicate that there is a structural change in bank competition after 2008. The main result, that herding is desirable because competition in the banking industry is low, is also robust to alternative profit measure and herding measure, which uses a longer sample period for identifying herding.

This study contributes to the literature by providing empirical evidence on the effect of herding on the competition and profitability of banks. Therefore, it complements the theory by Acharya and Yorulmazer (2007) that banks herd to increase the likelihood of a collective bailout position should default occur. In addition, existing empirical studies on bank herding have focused more on methods to detect herding and a single-country (Jain and Gupta, 1987; Uchida and Nakagawa, 2007). This study extends the discussion by providing multi-country evidence on the impact of herding on the competition and profit of banks. Therefore, this chapter adds in-depth evidence in support of the findings of previous studies on bank herding.

In addition, prior studies on the relationship between bank competition and profit performance have not considered herding as a possible explanatory factor. The majority of empirical studies on bank competition and performance have aimed to test the Structure-Conduct-Performance hypothesis (Hannan, 1991), which posits that market structure influences banks' competition and performance (profitability). These studies use market structure variables, such as concentration ratios, in addition to several bank-specific and macroeconomic factors to explain profit variation across banks (Athanasoglou, Brissimis and Delis, 2008; Mirzaei, Moore and Liu, 2013; McMillan and McMillan, 2016). However, Uchida and Nakagawa (2007) suggest that herding could be related to the lack of competiton among these banks. Therefore, this study contributes to the discussion on bank competition and performance by proposing herding as a factor that affects the competition and profit of banks.

The findings of this chapter suggest policies that increase competition in the banking industry should be encouraged. Higher competition would reduce banks' incentives to herd, therefore deterring herding and mitigating systemic risk. They also highlight the importance of adopting macroprudential regulations in association with microprudential regulations,[21] especially for countries that are proponents of market power-stability.[22]

[21] Macroprudential regulations are prudential regulations that aim to address system-wide risks that can build up across the banking sector as well as the procyclical amplification of these risks over time. Microprudential regulations aim to build the resilience of individual banking institutions to periods of stress (Basel Committee on Banking Supervision, 2011).

[22] The market-power stability hypothesis posits that market concentration and the resulting higher profit increases banks' charter value and thereby reduces excessive risk-taking (Cordella and Yeyati, 2002; Berger, Klapper and Turk-Ariss, 2009; Forssbæck and Shehzad, 2015). However, this study argues that lower competition in the banking sector allows banks to herd. Therefore, consistent with the findings in the second empirical chapter ("Systemic Risk Implications of Bank Herding"), systemic risk in the banking system increases.

4.2. Research Objective

The key objective of this chapter is to examine the effect of herding on the competition and profit of banks. As banks provide loans to the same industry, competition among them is likely to lead to a deterioration in their profit. Hence, examining the effect of herding on bank profit is important, as the risk of lower profit could countervail herding incentives.

4.3. Literature Review and Hypotheses Development

4.3.1. Bank Competition and Performance

The Structure-Conduct-Performance (SCP) hypothesis[23] posits that market structure influences banks' competition and performance (profitability). In particular, a small number of banks in a concentrated market may be able to collude or exploit their market power independently. These banks earn excessive profits by charging a higher loan rate and paying a lower deposit rate, causing an unfavourable outcome for consumers. The SCP hypothesis assumes market structure is exogenous.

Related to the SCP hypothesis, the dominant-bank hypothesis predicts that in an asymmetric banking structure, a bank has a dominant position in the market because of its technological edge over its competitors (VanHoose, 2017). The bank uses the technological advantage as a threat to engage in predatory pricing and deter entry. As long as the technology enables the dominant bank to set a loan price in excess of average costs, the threat is credible. This, in turn, increases the entry costs for small banks. When the costs are significant, the dominant bank can set its loan rate independently and smaller competitors act as price followers.

[23] For further details of the SCP hypothesis, see Hannan (1991).

Consistent with the hypothesis, Craig and Hardee (2007) find that the presence of large banks reduces SMEs' access to loans. Furthermore, lending by small banks does not necessarily increase loan availability for SME to its competitive levels. Pilloff (1999) also reports that when large and regionally important banks are present in a certain local market, competition in the respective market weakens. In addition, smaller banks in the market earn higher profits compared to those in markets without large banks. Similarly, Cyree and Spurlin (2012) find that when large banks exist in a rural market, the profitability of competing small banks increases. Moreover, small banks are more likely to survive the competition in the presence of large banks, because the latter are less efficient.

However, there are several empirical studies which do not support the SCP hypothesis. Using a sample of 2,700 state banks, Smirlock (1985) reports market concentration does not explain bank profit for U.S. based banks. Goldberg and Rai (1996) also fail to find a statistically significant relationship between profit and market concentration for the largest banks operating in 11 European countries from 1988 to 1991.

Furthermore, Lotti and Gobbi (2004), studying entry liberalisation in the Italian banking sector between 1992–2002, conclude that new locally established banks are more likely to exploit the deregulation compared to large banks operating in a different range of markets. They suggest that the lack of local business information is a factor that deters large established banks from expanding their market.

Several studies have also argued that smaller banks have a comparative advantage in lending to small businesses, especially those with limited access to financing and fixed-asset collateral. Banks providing loans to this category of debtor often depend on relationship lending to address asymmetric information problem (Petersen and Rajan, 1994; Boot, 2000; Ongena and Smith, 2001). Furthermore, Berger and Udell (2002) argue that only banks with a specific organisational structure can use this lending process more efficiently.

In particular, relationship lending requires the greater authority of loan officers, because information on small businesses is subjective and cannot be easily quantified. Therefore, other parts of the organisation find it more difficult to verify it. Information on borrowers is collected by loan officers through repeated interactions with the firm, owners, suppliers, customers and other related parties (Berger and Black, 2011). The information may include personal knowledge of the owner and management, the track record of project realisation and repayment on debt-like claims, and other subjective information regarding firm condition. Hence, loan officers are the repository of this soft information.

The delegation of authority to loan officers gives rise to the principal–agent problem within the bank and leads to costs to monitor loan officers’ behaviour. Accordingly, smaller banks with fewer managerial layers have a comparative advantage in this type of lending process compared to larger banks with several managerial layers.

Relationship lending also allows smaller banks to create product differentiation barriers and deter potential entrants (Dell'Ariccia, Friedman and Marquez, 1999; Marquez, 2002). In addition, because relationship lending involves the acquisition of private information, which is non-observable to other banks, small banks are able to extract informational rent from their borrowers (Sharpe, 1990; Sapienza, 2002).

Furthermore, the effect of competition on relationship lending is ambiguous. Several theoretical studies have argued that relationship lending is more prevalent when banks have market power (Sharpe, 1990; Petersen and Rajan, 1995). In particular, market power enables banks to extract future rents from borrowers, allowing intertemporal surplus sharing between banks and their borrowers. In other words, banks can subsidise new or distressed borrowers in earlier periods in exchange for a share of the rent in the future.

However, Boot and Thakor (2000) posit that relationship lending increases when competition in the banking industry intensifies. This is because the effect of interbank competition is more severe for transaction lending.[24] Hence, banks are induced to engage in relationship lending to partially insulate themselves from pure price competition. Nonetheless, the amount of rent banks can extract from their borrowers is lower compared to that in a less competitive market.

Similar to the theoretical research, related empirical studies have also come to conflicting conclusions. For example, Petersen and Rajan (1994) show that SME have more access to credits when banks have market power over their borrowers. However, Elsas (2005) finds that relationship lending increases with the level of bank competition. He suggests that banks maintain their market power through relationship lending in a competitive market.

The above literature on bank competition and profitability provides several hypotheses and empirical studies that may explain how herding affects the competition and profit of banks. Nonetheless, to the best of my knowledge, these studies have not

[24] Transaction lending is a lending process that is based on hard quantitative and, therefore, verifiable information such as: financial statements, collateral value and credit scores (Stein, 2002; Berger and Black, 2011).

analysed bank competition and profit within the context of herding explicitly. Several hypotheses are therefore developed and further elaboration on these is provided in the following section.

4.3.2. Hypotheses Development

The literature discussed previously suggests several possible arguments regarding the effect of herding on the competition and profit of banks. One is that competition among banks that herd is weaker compared to the rest of the industry (Uchida and Nakagawa, 2007). Therefore, herding is desirable because banks that herd can protect themselves from profit deterioration. To minimise competition and profit deterioration from herding, they may collude by engaging in relationship lending.

In particular, the informational advantage from relationship lending creates a product differentiation barrier and prevents outside competitors from entering the market (Dell'Ariccia, Friedman and Marquez, 1999; Marquez, 2002; Lotti and Gobbi, 2004). Several studies on collusion have argued that collusive behaviour is more sustainable when firms differentiate their products from those of their competitors (Chang, 1991; Ross, 1992; Häckner, 1995; Colombo, 2013). Market segmentation, because of product differentiation, implies that firms colluding gain less by cheating. In particular, firms that collude may cheat through a price cut. However, because the market is segmented, firms that cheat cannot easily capture the entire market. Therefore, collusion is easier to enforce when banks that herd engage in relationship lending.

When competition among banks that herd is weaker, the degree of profit persistence for banks that herd is higher compared to the industry. This leads to the first hypothesis:

H1: Competition among banks that herd is weaker compared to the rest of the industry. Therefore, profit is positively related to the degree of profit persistence conditional on herding.

Another possible argument is that even if competition among banks that herd is higher, herding is desirable because competition in the banking industry is low. More precisely, banks may herd by providing loans to the same industries (Acharya and Yorulmazer, 2007). As banks lend to the same industries, competition increases and profits may decline. Although it increases competition, herding may still be desirable if competition in the banking sector is low. Weaker industry competition allows banks to generate excess profit and compensates for the erosion in profit caused by herding (Acharya and Yorulmazer, 2008). This leads to the second hypothesis:

H2: Herding is desirable if the competition in the banking industry is low. Therefore, profit is negatively related to the degree of profit persistence conditional on herding and positively related to the degree of unconditional profit persistence.

The effect of increased competition from herding may differ between smaller and larger banks. Acharya and Yorulmazer (2007) posit that small banks have more incentive to herd compared to large banks. Consequently, too-many-to-fail affects small banks more than large banks. The findings in the first empirical chapter ("Bank Herding and its Determinants") and the second empirical chapter ("Systemic Risk Implications of Bank Herding") also support this theory.[25]

Furthermore, as explained in section 4.3.1 of this chapter, the dominant-bank hypothesis predicts that large dominant banks engage in predatory pricing to deter entry and maintain their market share (VanHoose, 2017). In addition, due to their scale economies in hard information processing, large banks are more inclined to engage in transaction lending (Stein, 2002; Carter, McNulty and Verbrugge, 2004). This exposes them to a larger adverse effect of increased competition on their profit (Boot and Thakor, 2000).

However, smaller banks have a comparative advantage in relationship lending due to their less hierarchical organisational structure (Berger and Udell, 2002). Hence, these banks may engage in the lending process to generate informational rent (Sharpe, 1990; Sapienza, 2002) and partially insulate themselves from pure price competition (Boot and Thakor, 2000; Elsas, 2005). This leads us to the third hypothesis:

H3: The adverse effect of increased competition on profit is larger (smaller) for banks that are followed by (follow) other banks.

[25] In the first empirical chapter, herding is more likely in countries with an asymmetric banking system. This suggests that herding is more likely to occur among banks with asymmetric sizes compared to those of a homogenous size. In the second empirical chapter, the number of banks that follow a particular bank is positively correlated with the size of the respective bank. This suggests that smaller banks are more likely to follow larger banks than the opposite.

The following section discusses the methodology used to empirically test the above three hypotheses.

4.4. Methodology

4.4.1. Estimation Method

As discussed in section 4.3.1 of this chapter, the SCP hypothesis (Hannan, 1991) posits that market structure influences bank competition and performance (profitability). Related empirical studies aim to test the hypothesis of whether there is a positive relationship between profit and market concentration, which may suggest the exploitation of market power. These methods assume that market structure reflects competition and market are at their long-run equilibrium. Several measures are used to indicate market structure including concentration ratio and the Herfindahl-Hirschman Index (HHI).

A competing hypothesis to the SCP is the Efficient-Structure (ES) hypothesis (Demsetz, 1973; Peltzman, 1977). The ES hypothesis posits that a positive relationship between profit and market concentration does not necessarily imply the exploitation of market power. Instead, the relationship may arise due to economies of scale and/or X-efficiency, with the latter potentially arising from superior management or production processes (Berger, 1995a). Banks that are more efficient can gain larger market share, leading to higher market concentration and profit. Hence, the hypothesis suggests that market concentration is endogenous, as both profit and market concentration are driven by efficiency. To address endogeneity, empirical studies on bank competition and performance have commonly included market share in their regressions (Degryse, Moshe and Steven, 2009).

Several additional empirical approaches have also been introduced in the literature to improve the measurement of banking competition. The methods can be categorised into two main approaches: 1) The New Empirical Industrial Organization (NEIO) and 2) POP models.

NEIO proposes direct methods for measuring competition, arguing that market structure may not accurately reflect the degree of competition. This is suggested by several empirical studies on bank competition and performance that show conflicting results using market concentration as their measure of bank competition (Degryse, Moshe and Steven, 2009).

One of the approaches within NEIO is the Lerner Index. The index is the difference between price and marginal cost relative to the price. A positive Lerner index or a positive deviation of output price from marginal cost represents the extent of market power. This measure, however, has been subject to several criticisms (Elzinga and Mills, 2011; Koetter, Kolari and Spierdijk, 2012). One is that the difference between output price and marginal costs may also reflect scale economies or the spread needed to cover fixed costs. Hence, a positive value may not necessarily indicate the presence of market power.

Another NEIO approach is proposed by Panzar and Rosse (1987). The Panzar and Rosse (1987) H-statistic measures the level of competition by identifying the elasticities of bank-specific revenues to their factor input prices. Perfect competition implies H-static equal to 1, as an increase in factor input prices leads to higher output prices but does not change the output volume. The presence of a monopoly is represented by a zero or negative value because an increase in factor input price may result, with either no effect or lower revenues. Monopolistic is indicated by values between 0 and 1, as revenue will change less than proportionally to changes in input prices.

However, Barbosa, de Paula Rocha and Salazar (2015), studying the Brazilian banking sector, argue that this approach does not consider the multi-product dimension of banking operations. Accordingly, the scope economies of banks that provide a broad range of services is not adequately captured by the H-statistic and the empirical model may underestimate the market power of these banks.

In addition, Goddard and Wilson (2009) argue that the H-statistic should be estimated using dynamic models to avoid misspecification bias. In particular, the microeconomic theory underpinning the use of the Panzar and Rosse test assumes market equilibrium conditions. In the short-run, however, markets may be out of equilibrium and the rate of convergence towards the long-run equilibrium may not be instantaneous. They find that bank performance in most countries is characterised by positive short-run persistence and partial adjustment. Accordingly, the H-statistic is prone to endogeneity when estimated using static models.

Furthermore, to capture the dynamic nature of the market and avoid misspecification bias that may arise from using static models, several studies have used the POP models (Goddard *et al.*, 2010, 2011; Amidu and Harvey, 2016; McMillan and McMillan, 2016). Proponents of the models argue that markets may be out of equilibrium at the point of observation. Consequently, an estimation result based on static models may not be useful for policy decision making. This is because the measured conduct and performance based on the result may not necessarily reflect their long-run equilibrium. Hence, to avoid endogeneity, related models should account for the dynamic characteristic of the market.

The POP models, initially developed by Mueller (1977), posit that competition eliminates excess profit in the short-run and profit converge towards their long-run equilibrium. However, when competition is less severe or profitable banks are able to deter market entrants, high profit can persist over longer periods. Therefore, profit converges slowly to their long-run equilibrium. The rate at which competition affects excess or less-than-normal profit in the short-run is measured by the degree of first-order autocorrelation in the time series of profit.

Therefore, to avoid the misspecification bias due to the possibility that the market may be out of equilibrium at the point of observation, this study uses dynamic panel-data in the following functional form:

$$\text{Profit} = f(\text{profit}_{t-1}, \text{interactions between profit and herding}_{t-1}, \text{control variables}_{t-1})$$

Nickell (1981) shows that OLS estimates of the lagged dependent variable's coefficient in a dynamic panel model are biased because of the correlation between the fixed effects and the lagged dependent variable. In addition, within transformation does not elimate dynamic panel bias because the lagged dependent variable is still correlated with the error term after transformation (Nickell, 1981; Roodman, 2009). To avoid bias, the parameters for the POP model above are estimated using system GMM (Arellano and Bover, 1995; Blundell and Bond, 1998) instead of fixed effect models.

Furthermore, Flannery and Hankins (2013) report that the effect of bias on the lagged dependent variable with fixed effects models is reduced only when: 1) the panel data has greater than 12 years of observation period; 2) there is more than one exogenous variable; 3) autocorrelation is low, and 4) the panel data is unbalanced with missing observations. Hence, although OLS estimators are more efficient compared to GMM, the GMM method is expected to provide consistent estimators for the short period dynamic panel data model.

System GMM uses first-difference to eliminate potential bias from time-invariant unobserved bank heterogeneity. In addition, lagged explanatory variables are used as instruments to further eliminate potential bias in the lagged dependent variable and to control for any simultaneity bias (Roodman, 2009; Wintoki, Linck and Netter, 2012). More precisely, the lagged level of the explanatory variables is used as instruments for the difference equations, and first difference is used as instruments for the level equations.

System GMM estimators involve estimating the following system of equations:

$$\begin{bmatrix} \pi_{i,t} \\ \Delta\pi_{i,t} \end{bmatrix} = \alpha + \begin{bmatrix} \pi_{i,t-1} \\ \Delta\pi_{i,t-1} \end{bmatrix}\delta + \begin{bmatrix} \pi_{i,t-1} * Leader_{t-1} \\ \Delta\pi_{i,t-1} * Leader_{t-1} \end{bmatrix}\gamma + \begin{bmatrix} \pi_{i,t-1} * Follower_{t-1} \\ \Delta\pi_{i,t-1} * Follower_{t-1} \end{bmatrix}\theta$$

$$+ \begin{bmatrix} \boldsymbol{x}'_{i,t-1} \\ \Delta\boldsymbol{x}'_{i,t-1} \end{bmatrix}\boldsymbol{\beta} + \begin{bmatrix} \boldsymbol{v}_{i,t} \\ \Delta\boldsymbol{v}_{i,t} \end{bmatrix} \qquad (4.1)$$

Where $\pi_{i,t}$ is the profitability of bank *i* at time *t*; $\pi_{i,t-1}$ is the one-period lagged profitability; $\pi_{i,t-1} * Leader_{t-1}$ and $\pi_{i,t-1} * Follower_{t-1}$ are the interactions between lagged profit and the different herding measures;[26] $\boldsymbol{x}_{i,t-1}$ is a k lag dimensional vector of other time-variant profit determinants, which includes: market structure, bank-specific characteristics and macroeconomic factors, and for any *t*, $\boldsymbol{x}_{i,t-1} \sim$ *i.i.d.* across banks $\boldsymbol{x}_i$; and $v_{i,t}$ is the error term. For any *t*, *s*, $v_{i,t}$ is independent of $v_{j,s}$ when i ≠j.

[26] The herding measures are explained further in section 4.4.3 of this chapter.

The degree of unconditional profit persistence, δ, measures the level of competition in the banking industry. When competition is low, δ is close to 1. This means that short-term profit converges slowly to its long-run level. However, when competition is high, the estimates are close to 0. This means any excess profit in the short-run is eliminated quickly.

Furthermore, γ (θ) measures the degree of profit persistence conditional on herding for banks that are followed by (follow) other banks. A positive γ and θ means that the level of competition (the degree of profit persistence) is lower (higher) for banks that herd compared to the industry. However, when herding increases competition, the degree of profit persistence conditional on bank herding or γ and θ is negative.

The model parameters in equation (4.1) are estimated using a two-step system GMM estimator with Windmeijer (2005) bias-corrected standard errors. The use of corrected standard errors is intended to account for the bias of the traditional two-step GMM standard errors in dynamic panel-data models (Roodman, 2009). The treatment assumes that errors are not correlated across individuals. Hence, to make the assumption of no correlation in the error terms more likely to hold, year dummy variables are included in the regression.

Furthermore, the consistency of the system GMM estimators depends on instruments' validity and the assumption that the error terms are not correlated holds. Two specification tests are used to test the consistency of the parameter estimates. The first is the Hansen test of over-identifying restrictions, which tests the null hypothesis that the instruments are exogenous. The second is a test for autocorrelation, which tests the null hypothesis of no autocorrelation in the error terms. The latter test is specific to system GMM, because the method uses the lagged dependent variable as one of the instruments. When autocorrelation exists, the instruments may be correlated with the error terms, thereby undermining the instruments' validity. However, because $\Delta v_{i,t}$ is computationally related to $\Delta v_{i,t-1}$ through $v_{i,t-1}$, first-order autocorrelation between $\Delta v_{i,t}$ and $\Delta v_{i,t-1}$ is expected. Hence, to test for autocorrelation in the levels, the second-order autocorrelation in differences is use instead. This identifies correlation between $v_{i,t-1}$ in $\Delta v_{i,t}$ and $v_{i,t-2}$ in $\Delta v_{i,t-2}$ (Roodman, 2009).

The first hypothesis that: "*competition among banks that herd is weaker compared to the rest of the industry. Therefore, profit is positively related to the degree of profit persistence conditional on herding*" can be supported if $\gamma > 0$ and $\theta > 0$. Positive values of γ and θ suggest the degree of profit persistence is higher for banks that herd compared to the industry.

The second hypothesis that: "*herding is desirable if the competition in the banking industry is low. Therefore, profit is negatively related to the degree of profit persistence conditional on herding and positively related to the degree of unconditional profit persistence*" can be supported when $\gamma \leq 0$ and $\theta \leq 0$ and δ is close to 1.

Negative values of γ and θ indicate lower degree of profit persistence for banks that herd. This suggests that herding increases bank competition. In addition, close to one δ implies that the rate in which short-term profit converges to its long-run level is slow, indicating a low level of competition in the banking industry. Furthermore, when $\delta \geq |\gamma|$ and $\delta \geq |\theta|$, excess profit from lower industry competition allows banks to compensate for lower profit from herding.

The third hypothesis that: "*the adverse effect of increased competition on profit is larger (smaller) for banks that are followed by (follow) other banks*" can be supported when $\gamma \leq 0$ and $\theta \leq 0$ and $\gamma < \theta$.

4.4.2. Measures of Profit

Income after tax is used as a measure of profit to control for tax rate differences across the sample countries. This approach is also consistent with the argument that market entry and exit is determined by after-tax income (Goddard *et al.*, 2011). Two profit measures are used: ROA and ROE; the latter is used to check for robustness. ROA is defined as net income divided by average total assets. Data on ROA are obtained from Orbis Bank Focus. To examine the effect of herding on the competition and performance of banks, profit is regressed on the interaction between its lag and the bank-level herding measures. The herding measures used in this study are consistent with those proposed in chapter 3 ("Systemic Risk Implications of Bank Herding"). Further explanation on the measures is provided in the next section. In addition, other profit determinants are included in the regression as control variables.

4.4.3. The Interaction between Lagged Profit and Bank Herding

The interaction between one period lag profit and the bank-level herding measures are used to examine the effect of herding on the competition and performance of banks. As in a previous chapter ("Systemic Risk Implications of Bank Herding"), this chapter also uses two measures of bank-level DGC to capture different dimensions of herding. The first measure (DGC Leader) captures the extent of herding or mimicking of bank

i by other banks j, or bank i acting as leader in the herd. This is computed as the fraction of statistically significant $\beta_{j,i}$ among $N - 1$ relationships in the following form:

$$DGC\ Leader \equiv \frac{1}{N-1}\sum_{j=1}^{N-1}(i \to j) \qquad (4.2)$$

The second measure (DGC Follower) captures the extent of herding or mimicking of other banks j by bank i, or bank i acting as follower in the herd, in the following form:

$$DGC\ Follower \equiv \frac{1}{N-1}\sum_{j=1}^{N-1}(j \to i) \qquad (4.3)$$

Both DGC measures exclude relationships with feedback effects.[27] As discussed in chapter 2 ("Bank Herding and its Determinants"), Granger's procedure involves running a regression in the form of equation (2.16) and (2.17). Consistent with the previous two chapters (chapter 2 and chapter 3), commercial banks are required to have at least 36 monthly stock returns within a 5-year observation period to be included in the sample. The method uses adjusted stock return as the dependent variable to control for heteroscedasticity in the form of equation (2.18).

Furthermore, as discussed in chapter 2 ("Bank Herding and its Determinants"), the herding measures can be misleading when a country only has a few listed banks in the sample. Therefore, consistent with the requirements listed in chapter 2 ("Bank Herding and its Determinants") and chapter 3 ("Systemic Risk Implications of Bank Herding") countries are required to have at least five listed banks to calculate the

[27] As explained in the first empirical chapter ("Bank Herding and its Determinants"), consistent with the definition of herding in this study, a one-way test is used to reduce the possibility of identifying spurious herding as active herding. Jain and Gupta (1987) argue that the two-way test may indicate several possibilities: (i) there is a feedback effect in which both banks consider each others' behaviours when making lending decisions and (ii) the lending or investment decisions are the result of a similar credit or business analysis approach. The latter, however, does not necessarily indicate the existence of herding behaviour.

measure to improve data representativeness. Data to compute herding measures are obtained from Datastream.

The list of countries and the number of banks for each country included to generate the DGC or the herding measures is presented in Table 4.1. The table also shows that the sample selection is not dominated by banks from any particular country. Although a higher number of banks from the U.S. or Japan is observed, the size is relatively insignificant when compared to the total, due to the large number of countries in the sample.

The DGC measures are based on the assumption that, in efficient markets, current stock prices reflect information related to the financial institutions (Krainer and Lopez, 2004; Gropp, Vesala and Vulpes, 2006), including their interconnectedness from herding.[28] As explained in chapter 2 (“Bank Herding and its Determinants”), to increase the likelihood of a collective bailout position should default occur, banks must synchronise their asset allocation and funding strategies.[29] This, in turn, causes the risk characteristics of these banks to become similar. Accordingly, as herding involves the mimicking of a bank’s strategy by another bank, an idiosyncratic shock that affects a leader bank also affects other banks in the herd.

As explained in chapter 2 (“Bank Herding and its Determinants”), the DGC measure is robust to contemporaneous common shocks. As a robustness check, Billio *et al.* (2012) use stock market return to control for common-factor exposure in the Granger causality test. They report similar results with the main test, which does not

[28] Similarly, Silva-Buston (2019) uses the residuals of the regression of MES, which is computed using stock return, to identify bank herding. Instead of using residuals, bank herding in this study is measured directly based on the Granger causality test.
[29] This approach is consistent with research on systemic risk, which argues that, in addition to the asset side, the liabilities side of banks can play an important role in triggering systemic risk or joint bank defaults (Allen *et al.*, 2012; Farhi and Tirole, 2012; Agur, 2014;).

use the variable. The estimations reported in chapter 2 ("Bank Herding and its Determinants") also control for the possibility of contemporaneous unintentional herding by including stock market return in the DGC models. According to the result, the relationship between the DGC measures and stock market return is statistically insignificant.

In addition, Acharya and Yorulmazer (2007) suggest that lower profit due to herding could countervail herding incentives in their theoretical model. Therefore, reverse causality may exist between profit and herding. More precisely, as competition increases and profit declines due to herding, banks may have less incentive to herd. This in turn may reduce the number of banks that herd. To address simultaneity bias, the interaction between profit and the herding measures are treated as endogenous variables in the regression.

4.4.4. Control Variables

1. Market Structure

Market structure is included in the regression to control for the effect of the variable on bank competition and profit. According to the SCP hypothesis, a small number of banks in a concentrated market may collude or exploit their market power independently to earn excess profit. Furthermore, Acharya and Yorulmazer (2008) suggest that the herding incentive is more likely to be stronger in concentrated markets. Hence, the variable is also included to control for the spurious relationship between profit and herding due to market structure.

Consistent with empirical studies on bank competition and performance, as explained in section 4.4.1 of this chapter, the HHI is used to measure market structure.

The variable is defined as the sum of squared market share of all banks, in the following form:

$$HHI = \sum_{i=1}^{N} s_i^2 \qquad (4.4)$$

Where s_i is the market share of bank *i* defined as the bank's assets as a percentage of the total banking industry assets in a country, and *N* is the number of banks.

Furthermore, the ES hypothesis argues that a positive relationship between market concentration and profit does not necessarily suggest an exploitation of market power. Banks that are more efficient can gain larger market share, leading to higher market concentration and profit. Hence, market concentration is endogenous, as profit and market concentration are both determined by efficiency. Accordingly, following other related empirical studies, market share is included in the regression to control for the effect of market structure on herding and profit that may be related to bank efficiency.

Following Mirzaei, Moore and Liu (2013), if the coefficient of HHI in the regression (equation 4.1.) is above 0 and that for market share is equal to zero, then the traditional SCP hypothesis can be supported. In other words, market structure affects bank competition and profit. However, when the coefficient of HHI is equal to 0 and that for market share is higher than 0, the ES hypothesis prevails (Degryse, Moshe and Steven, 2009; Mirzaei, Moore and Liu, 2013). In other words, banks that have a larger market share are more efficient and, therefore, generate higher profit.

As explained in section 4.3.1 of this chapter, prior empirical studies have reported mixed evidence on the relationship between profit and market structure. Hence, there are no clear prior expectations of the relationship in this study. Data to compute both

HHI and market share are collected from Orbis Bank Focus. Listed and unlisted banks total assets are both used to compute the two measures.

2. *Bank-Specific Characteristics*

Asset size: Berger and Udell (2002) argue that small banks with closely held organisational structures and few managerial layers perform better when dealing with soft information related to relationship lending. In turn, relationship lending allows banks to acquire private information and extract informational rents from their borrowers (Sharpe, 1990; Sapienza, 2002).

However, large banks may obtain scale economies from reduced costs of loan monitoring. They may also obtain scope economies from product diversification, as their size allows them to access markets which small banks cannot exploit. Hence, large banks may generate higher profit compared to small banks. Several studies have found evidence of scale economies for large banks (Berger and Humphrey, 1997; Altunbaş *et al.*, 2001). Furthermore, the relationship between profit and size may eventually become inversely related. This is because extremely large banks may experience scale diseconomies due to higher management costs, such as agency costs and bureaucratic costs (Athanasoglou, Brissimis and Delis, 2008; Mirzaei, Moore and Liu, 2013).

Accordingly, there is no clear prior expectation on the relationship between profit and bank size, and this remains an empirical question. Bank size is measured by the natural logarithm of total assets. To capture the nonlinear relationship between profit and bank size due to scale diseconomies, a quadratic term of bank size is included in the regression. Data on total assets are acquired from Orbis Bank Focus.

Leverage: several studies have argued that capital reduces the probability of bank default (Merton, 1977a; Coval and Thakor, 2005; Mehran and Thakor, 2011). In turn, according to the bankrupty costs hypothesis, as default risk increases uninsured debt holders will demand banks hold more capital or pay insurance costs against the higher default probability (Berger, 1995b). The insurance cost is reflected in the risk premium charged by uninsured debt holder. Consequently, banks with a lower capital ratio are expected to generate a lower profit due to higher uninsured debt rates.

An alternative theory to the expected bankruptcy costs hypothesis is the signalling hypothesis (Ross, 1977). This assumes that managers have private information on their firms' future cash flows and own shares of the firm, which are not tradable. Given these set of assumptions, managers can credibly signal the true value of their firms through their capital decision. More precisely, banks that expect to perform better may signal this information to the market by increasing their leverage.

Consistent with the two conflicting hypotheses, empirical studies that use capital ratios as a determinant of bank profit have generated mixed results (Molyneux and Thornton, 1992; Goddard *et al.*, 2010; Chronopoulos *et al.*, 2015). Hence, there is no prior expectation on the relationship between profit and capital ratio, and this remains an empirical question. In addition, the signalling hypothesis suggests that capital also depends on profit expectations. Accordingly, following Athanasoglou, Brissimis and Delis (2008), capital is treated as not strictly exogenous in the regressions to address endogeneity. Capital ratio is measured by equity to total assets, and data on the variables are acquired from Orbis Bank Focus.

Liquidity: banks that have lower liquidity (i.e. a high proportion of loans to total assets) are more likely to incur losses to meet large unexpected liquidity needs. Losses may occur due to forced assets liquidation or borrowing from the secondary market at a fire-sale premium. One of the reasons loans are illiquid is because relationship-specific skills are required to collect loans (Diamond and Rajan, 2001). Hence, this suggests that profit is negatively related to loans to total assets. Required data are obtained from Orbis Bank Focus.

Income diversification: the variable is included to capture the relationship between profit and diversification. Previous studies have suggested that diversification does not necessarily generate higher risk-adjusted returns for banks (DeYoung and Rice, 2004; Stiroh and Rumble, 2006; Laeven and Levine, 2007). However, McMillan and McMillan (2016) find that banks with diversified earnings generate higher profit. Hence, there is no prior expectation on the relationship between profit and income diversification. Non-interest income to total operating revenue is used to measure this variable. Data required to measure income diversification are collected from Orbis Bank Focus.

Loan risk: to control for profit variation due to loan risk, the ratio of non-performing loans to total assets and the ratio of net charge-offs to total loans are both used as a comparison. A higher ratio may indicate a higher loan risk. Bikker and Hu (2002) argue that deterioration in loan quality reduces the profit generated from lending. In addition, related to net charge-offs to total loans, the variable is treated as endogenous. This is because periods of economic booms may induce banks to take a higher risk by lowering their lending standards to meet short-term profit targets. Hence, when economic conditions worsen and profit deteriorates, banks set large net charge-offs to offset excessive risk taking during growth periods (Berger and Udell, 2004; Ruckes, 2004). The data required to measure loan risk variables are obtained from Orbis Bank Focus.

3. Macroeconomic Factors

Favourable macroeconomic conditions provide banks with profitable investment opportunities (Albertazzi and Gambacorta, 2009). Chronopoulos *et al.* (2015) also find evidence that bank profit is procyclical, increasing during economic booms and declining during economic downturns. However, the investment opportunities offered by higher economic growth may increase competition among banks (Ruckes, 2004; Goddard *et al.*, 2011; Amidu and Harvey, 2016) leading to an inverse relationship between profit and GDP growth. Hence, there is no prior expectation for the relationship between bank profit and GDP growth.

Mirzaei, Moore and Liu (2013) argue that when banks expect inflation to increase, they adjust lending rates more than deposit rates and preserve real profit. Several studies have also found that bank profit is positively related to inflation rate (Molyneux and Thornton, 1992; Amidu and Harvey, 2016). Hence, inflation is included as a control factor in the regression. Data on both macroeconomic variables are acquired from the International Monetary Fund World Economic Outlook database as of October 2019.

4.5. Data

4.5.1. Sample

The sample used in this study includes publicly listed commercial banks across 53 countries that were active during the period 2013–2019, consisting of 3,483 unbalanced bank-year panel data, covering 626 banks over 7 years. The short observation period allows for the assumption that the unobserved bank heterogeneity are time-invariant more likely to hold. Furthermore, to address the endogeneity issue related to dynamic panel data with short observation period, as explained in section 4.4.1, the estimation method of system GMM is used to estimate the parameters.

4.5.2. Summary Statistics

Table 4.2 shows the summary statistics of banks' ROA (a measure of profit) and its determinants. ROE is also used as a measure of profit to examine the sensitivity of results to the choice of profit measure. As shown from the table, the sample represents a heterogeneous cross section of banks and countries in respect of the herding measures, bank-specific characteristics, market structure indicators, and macroeconomic factors. The observed standard deviations of these measures confirm the variations across banks and countries.

The DGC measures of herding in this table support the argument that banks herd to increase the likelihood of a collective bailout position should default occur, as the positive value of these measures indicate a possibility of correlated risk-taking from bank herding. The means of both measures are also significantly larger compared to the median. This suggest that the distribution of the measures is skewed to the right, with few banks having a large number of connections from herding.

Following several studies on profit persistence (Goddard *et al.*, 2011; Chronopoulos *et al.*, 2015), ROA are winsorised at the top and bottom 1% level to reduce the influence of potential outliers. Furthermore, extreme values are observed for other variables, particularly in *Non-Performing Loans to Total Assets*$_{t-1}$, *Net Charge-Offs to Loans*$_{t-1}$ and *Inflation*$_{t-1}$.

Most outliers in *Non-Performing Loans to Total Assets*$_{t-1}$ data are related to banks in Ukraine. The average *Non-Performing Loans to Total Assets*$_{t-1}$ for these banks in the sample is 28.13%, far exceeding the sample average of 3.71%.[30] Extreme values related to *Net Charge-Offs to Loans*$_{t-1}$ are contributed by several banks from different countries, suggesting that these data are due to idiosyncratic shocks. The portion of extreme values related to the variable in the sample is less than 2%. Extreme values in *Inflation*$_{t-1}$ are from Venezuela.[31]

Table 4.3 reports pairwise correlations between bank performance, the herding measures, the interactions between herding and bank performance, and other known determinants of profit. The relationships between *ROA* and the interaction terms, *ROA*$_{t-1}$ *x DGC_Leader*$_{t-1}$ and *ROA*$_{t-1}$ *x DGC_Follower*$_{t-1}$, are both positive and significant at 1% level. This may be, however, due to the inclusion of lagged profit, *ROA*$_{t-1}$, in the interaction terms.

DGC_Leader$_{t-1}$ is positively correlated with *Log Total Assets*$_{t-1}$ and *Market Share*$_{t-1}$, at the 5% and 1% levels of significance respectively. However, *DGC_Follower*$_{t-1}$ is negatively correlated with *Log Total Assets*$_{t-1}$ at the 1% level. These correlations suggest banks that are followed by (follow) other banks have larger

[30] The Ukrainian banking system is historically characterised by a large number of banks that operate as the financing source of oligarchic owners or their affiliated companies (Buckley and Olearchyk, 2017). Consequently, these banks are commonly engaged in related-party transactions and tend to exhibit poor governance. The banking condition worsened by military conflicts in parts of eastern Ukraine that started in 2014, leading to an economic crisis in 2015 (Oesterreichische Nationalbank, 2017). The International Monetary Fund’s World Economic Outlook database shows that the GDP growth in Ukraine declined to -6.55% in 2014 and worsened further to -9.77% in 2015. Data from the World Bank show that the banking system NPL ratio in 2015 reached 28% from 19% in 2014. The ratio has continued to increase to 55% in 2017.

[31] During the sample period, Venezuela experienced political uncertainty and hyperinflation. According to the International Monetary Fund World Economic Outlook database as of October 2019, the country's inflation rate, which has been over 50 percent since 2013, reached 863 percent in 2017.

(smaller) asset size and market share. They also confirm the theory of Acharya and Yorulmazer (2007) that small banks follow larger banks.

In addition, the correlation between *ROA* and *Non-Performing Loans to Total* $Assets_{t-1}$ is negative and significant at the 1% level. The relationships are consistent with the argument of Bikker and Hu (2002) that a deterioration in loan quality reduces profit from lending. Similarly, the correlation between *ROA* and $Inflation_{t-1}$ is positive and significant, consistent with several studies that have suggested inflation increases bank profit (Molyneux and Thornton, 1992; Mirzaei, Moore and Liu, 2013; Amidu and Harvey, 2016).

4.6. Results

The key objective of this chapter is to examine the effect of herding on the competition and profit of banks. To address this key question three hypotheses, as noted earlier, are tested. Estimates reported in Table 4.4 column (1) aim to address the three hypotheses with ROA as the dependent variable. The estimates in column (1) reject the first hypothesis that "*competition among banks that herd is weaker compared to the rest of the industry. Therefore, profit is positively related to the degree of profit persistence conditional on herding*" in favour of the second hypothesis. In particular, the results suggest, "*herding is desirable if the competition in the banking industry is low. Therefore, profit is negatively related to the degree of profit persistence conditional on herding and positively related to the degree of unconditional profit persistence.*"

The coefficient for ROA_{t-1} *x* DGC_Leader_{t-1} and ROA_{t-1} *x* $DGC\_Follower_{t-1}$ are -0.017 and -0.005 statistically significant at the 1% and 10% levels respectively. The negative sign of the coefficient indicates that the degree of profit persistence is lower for banks that herd. In addition, the degree of unconditional profit persistence, i.e. the coefficient of ROA_{t-1}, is 0.609 (above 0.5) and statistically significant at 1%. This suggests that competition in the banking industry is low. The size of the coefficient of unconditional profit persistence, ROA_{t-1}, is also larger compared to those of ROA_{t-1} x DGC_Leader_{t-1} and ROA_{t-1} x $DGC\_Follower_{t-1}$. The larger coefficient for ROA_{t-1} suggests that excess profit in the short-run from lower industry competition allows banks to compensate for lower profit from herding.

The evidence of the low level of competition among the banks is consistent with the findings reported in earlier studies such as Chronopoulos *et al.* (2015) and McMillan and McMillan (2016). They argue that competition level in the banking system has weakened after the financial crisis of 2008. Chronopoulos *et al.* (2015) suggest that during the crisis, governments' intervention to limit spillover effects may have prioritized stability over competition. In particular, government support to larger banks increased banking concentration and reduce competition. Spokeviciute, Keasey and Vallascas (2019) also provide evidence that banks' efficiency following the global financial crisis has remained significantly below the pre-crisis level, suggesting less competition in the banking system.

The estimates (Table 4.4 column 1) also support the third hypothesis that "*the adverse effect of increased competition on profit is larger (smaller) for banks that are followed by (follow) other banks"*. This is indicated by the negative and relatively larger coefficient of ROA_{t-1} x DGC_Leader_{t-1} compared to that of ROA_{t-1} x $DGC\_Follower_{t-1}$. The coefficient of ROA_{t-1} x DGC_Leader_{t-1} is -0.017 and statistically significant at the 1% level and that of ROA_{t-1} x $DGC\_Follower_{t-1}$ is -0.005 and significant only at 10%.

This finding is consistent with several studies on bank competition and profit. The dominant-bank hypothesis posits that larger banks engage in predatory pricing to deter competition and maintain their market share (VanHoose, 2017). Larger banks also depend more on transaction lending due to their scale economies (Stein, 2002; Carter, McNulty and Verbrugge, 2004). Therefore, these banks experience a more severe effect of increased competition (Boot and Thakor, 2000). However, smaller banks may use relationship lending to generate informational rent (Sharpe, 1990; Sapienza, 2002) and partially insulate themselves from pure price competition (Boot and Thakor, 2000; Elsas, 2005).

The finding supports the theory of Acharya and Yorulmazer (2007) that smaller banks have more incentive to herd and consequently, too-many-to-fail affects small banks more than large banks. The result is also consistent with the findings reported in the second and third chapters of this thesis. Evidence reported and discussed in chapter 2 ("Bank Herding and its Determinants") suggests that herding is more likely in countries with an asymmetric banking system, whereas chapter 3 ("Systemic Risk Implications of Bank Herding") shows that the number of banks that follow a particular bank are positively correlated with the size of the bank. This indicates that small banks are more likely to follow larger banks than the opposite.

Furthermore, the estimates show that the coefficients of HHI_{t-1} are not statistically significant but that of $Market\ Share_{t-1}$ (0.020) is significant at the 1% level (Table 4.4 column 1). Hence, the findings suggest that banks with a larger market share are more efficient and, therefore, generate higher profit. As explained in section 4.4.4 of this chapter, market structure measured by HHI_{t-1} is included in the regression to control for the spurious relationship between profit and herding due to market concentration. The SCP hypothesis posits that a small number of banks in a concentrated market may collude or exploit their market power independently to generate excess profit. In addition, Acharya and Yorulmazer (2008) suggest that the herding incentive is likely to be stronger in concentrated markets. Hence, market structure may affect both bank profit and herding, causing a spurious relationship between the profit and herding.

Moreover, according to the ES hypothesis, a positive relationship between market concentration and profit does not necessarily suggest the exploitation of market power. Banks that are more efficient can gain larger market share, leading to higher market concentration and profit. To control for the effect of market structure on herding and profit that may be related to bank efficiency, $Market\ Share_{t-1}$ is also included in the regression. The estimates in Table 4.4 column (1) show a significant and positive coefficient of $Market\ Share_{t-1}$ and an insignificant coefficient of HHI_{t-1}. These findings support the prediction of the ES hypothesis in contrast to that of the SCP hypothesis.

As explained in section 4.4.1 of this chapter, the consistency of system GMM estimators depends on the validity of the instruments used and the assumption that the error terms are not correlated holds. Two specification tests are used to examine the consistency of the estimators. The first is the Hansen test of over-identifying restrictions, which tests the null hypothesis that the instruments are exogenous. The second is a test for autocorrelation, which tests the null hypothesis of no autocorrelation in the error terms.

The results of these tests are presented at the bottom of Table 4.4 column (1). The Hansen test of over-identifying restrictions (*Hansen*) shows that there is no evidence to reject the null hypothesis that the instruments are exogenous. The result for the second-order autocorrelation tests (*AR(2)*) suggests that there is no evidence to reject the null hypothesis of no autocorrelation in the error terms. Therefore, both the Hansen test and the second-order autocorrelation test suggest that the estimates, in general, are consistent.

Columns (2)–(4) of Table 4.4 reports the result of three additional ROA models that differ in the set of control variables used to measure macroeconomic factors and loan risk. In particular, the model in column (2) uses one year lagged inflation, $Inflation_{t-1}$, in addition to GDP growth in column (1) as the measures of macroeconomic condition.[32] The model in column (3) uses the ratio of net charge-offs to total loans, $NCO\ to\ Loans_{t-1}$, as the loan risk measure instead of non-performing loans to total assets ($NPL\ to\ Total\ Assets_{t-1}$) in column (1). Finally, the model in column (4) uses $NCO\ to\ Loans_{t-1}$ and includes $Inflation_{t-1}$ as the measures of loan risk and macroeconomic condition respectively. The results of these additional models show that the findings reported in Table 4.4 column (1) are relatively robust to alternative measures of macroeconomic factors and loan risk.

The coefficients of $ROA_{t-1}\ x\ DGC\_Leader_{t-1}$ in columns (2)–(4) and that of $ROA_{t-1}\ x\ DGC\_Follower_{t-1}$ in column (2) are negative and statistically significant. These estimates indicate that the banks that herd experience higher competition and lower profit. The coefficients of ROA_{t-1} are between 0.597 and 0.682, and statistically significant at the 1% level across the models, suggesting that the level of competition in the banking industry is low. The size of the coefficient of ROA_{t-1} is also larger

[32] Several studies on bank competition and performance that use the POP model employ different sets of macroeconomic factors as their control variables. For example, Chronopoulos *et al.* (2015) and McMillan and McMillan (2016) both use GDP growth. However, Amidu and Harvey (2016) use both GDP growth and inflation.

compared to those of ROA_{t-1} x DGC_Leader_{t-1} in columns (2)–(4) and that of ROA_{t-1} x $DGC\_Follower_{t-1}$ in column (2). This indicates that excess profit from lower competition in the banking industry allows banks to offset their lower profit from herding.

The results reported in columns (2)–(4) (Table 4.4) also support the third hypothesis that "*the adverse effect of increased competition on profit is larger (smaller) for banks that are followed by (follow) other banks*". This is indicated by the negative and relatively larger coefficients of ROA_{t-1} x DGC_Leader_{t-1} compared to those of ROA_{t-1} x $DGC\_Follower_{t-1}$. More precisely, the coefficients of ROA_{t-1} x DGC_Leader_{t-1} in columns (2)–(4) are between -0.047 and -0.018, statistically significant at the 1% level. However, the coefficients of ROA_{t-1} x $DGC\_Follower_{t-1}$ in column (2) is -0.006 and significant at the 5% level, and those in columns (3)–(4) are both insignificant.

The results also support the ES hypothesis, which argues that banks with larger market share are more efficient and, therefore, generate higher profit. In particular, the coefficients of market structure, HHI_{t-1}, are not statistically significant. However, those of market share, *Market* $Share_{t-1}$, are statistically significant.

The coefficients of $LogTotalAssets_{t-1}$ (0.715 and 0.743) reported in columns (3)–(4) of Table 4.4 are statistically significant at 5%. In addition, the coefficients of $LogTotalAssets\_sq_{t-1}$ in columns (2)–(4) are between -0.024 and -0.013, both statistically significant at the 5% and 10%. The results, providing evidence of scale economies for large banks, is consistent with the findings of Berger and Humphrey (1997) and Altunbaş *et al*. (2001), and scale diseconomies of extremely large banks is consistent with the views of Athanasoglou, Brissimis and Delis (2008) and Mirzaei, Moore and Liu (2013).

In addition, the coefficient of *NPL to Total Assets*$_{t-1}$ in column (2) (-0.018) is significant only at the 10% level, similar to that reported in column (1). This provides some support to the argument of Biker and Hu (2002) that deterioration in loan quality reduces profit generated from lending. The result in columns (2) and (4) of Table 4.4 shows that *GDP Growth*$_{t-1}$ is positively related to bank profit and significant only at the 10% level. This is, to some extent, consistent with the argument that favourable macroeconomic conditions provide banks with profitable investment opportunities and, therefore, bank profit is procyclical (Albertazzi and Gambacorta, 2009; Chronopoulos *et al.*, 2015).

4.7. Further Tests

4.7.1. Subsample Analysis

As discussed in the previous section (4.6. Results), the observed low competition in banking industry may be related to governments' priority of stability over competition. In particular, government support for larger banks during the global financial crisis in 2008 increased banking concentration and reduced competition (Chronopoulos *et al.*, 2015). Accordingly, the results of this study may have been affected by U.S. and Western Europe countries, which are directly influenced by the global financial crises and where most global systematically important banks originated.[33] To further examine whether the results are consistent across countries, an

[33] A list of global systematically important banks is available at https://www.fsb.org/work-of-the-fsb/policy-development/addressing-sifis/global-systemically-important-financial-institutions-g-sifis/

analysis is performed using a subsample of non-U.S. and non-Western Europe countries in the regressions.

As presented in Table 4.5, the subsample results are consistent with the full sample. In particular, the results support the second hypothesis that herding is desirable because of weak competition in the banking industry. The coefficients of ROA_{t-1} x DGC_Leader_{t-1} in columns (1)–(4) are all negative and statistically significant. These suggest that herding increases competition and reduces profit, especially for banks that are followed by others. The coefficients of ROA_{t-1} are between 0.593 and 0.683, and statistically significant at the 1% level across the models, suggesting that the level of competition in the banking industry is low. The size of the coefficient of ROA_{t-1} is also larger compared to that of ROA_{t-1} x DGC_Leader_{t-1}, indicating that lower competition in the industry allows banks to generate excess profit to compensate for the lower profits from herding.

The results reported in Table 4.5 also support the third hypothesis, as indicated by the negative and relatively larger coefficients of ROA_{t-1} x DGC_Leader_{t-1} compared to those of ROA_{t-1} x $DGC\_Follower_{t-1}$. More precisely, the coefficients of ROA_{t-1} x DGC_Leader_{t-1} are between -0.040 and -0.019, statistically significant at the 1% level. However, the coefficients of ROA_{t-1} x $DGC\_Follower_{t-1}$ are statistically insignificant. The findings suggest that the effect of herding on competition and profit is larger for banks who are leaders compared to those that follow others.

The consistent findings with those of the full sample support the argument of strong globalisation in the financial industry (López-Espinosa *et al.*, 2012). Lower global competition due to government intervention in major economies, which were directly affected by the global financial crisis, may have also affected domestic competition in other countries. According to the IMF (2015), following the crisis, global banks reduced their international exposure. This may have led to an increased role of less efficient regional and local banks to fill the void in financial services previously provided by the global banks.

4.7.2. Financial Crisis and Structural Change in Bank Competition

Two structural break tests, the dummy variable based test and Chow test, are performed to examine whether the result is consistent with earlier studies that suggested banking competition is weaker after 2008 (Chronopoulos, Liu, McMillan and Wilson, 2015; McMillan and McMillan, 2016). Owing to the limited data availability prior to 2012 in Orbis Bank Focus, data for the period between 2005–2011 (7 years) are collected from CapitalIQ for this particular test.

As the HHI is computed using the former database, the variable is replaced in this test by market concentration. The latter variable is defined as the size of the largest three banks in terms of total assets relative to the size of the banking sector total assets. Market concentration data for each county are collected from the World Bank Financial Structure Dataset as of October 2019.

Another implication of using CapitalIQ is that data on bank market share are unavailable. Similar to HHI, the variable is computed using listed and unlisted banks total assets. However, CapitalIQ provides mostly data of listed banks. Accordingly, the effect of market structure on herding and profit that may be related to market share is not controlled for in the regressions. The following section discusses the results of both tests.

1. *Dummy Variable Based Test*

A post crisis dummy is included in the main regressions and set equal to 1 for periods after 2008 and 0 otherwise. Similarly, the parameters in this test are estimated using a two-step system GMM estimator with Windmeijer (2005) bias-corrected standard errors. Year dummy variables are included in the regression to make the assumption of no correlation in the error terms more likely to hold.

As shown in Table 4.6 columns (1)–(2), the coefficients of the interaction between lag profit and post crisis dummy (*ROA_post*) are all positive and significant. These results support the argument that competition in the banking industry (unconditional profit persistence) is weaker (higher) following the crisis.

Table 4.6 columns (3)–(4) show some evidence that competition for banks that herd (conditional profit persistence) post crisis is weaker (higher). In particular, the coefficients of $ROA\_post \times DGC\_Leader_{t-1}$ and $ROA\_post \times DGC\_Follower_{t-1}$ are both positive and significant at the 5% and 10% levels respectively.

2. *Chow Test*

As an alternative to the dummy variable based test earlier, a Chow test (Chow, 1960) is performed to examine whether competition in the banking industry has declined following the 2008 crisis. The test assumes that the variance of the full period regression is equal to the sum of the variance of the subsample periods regression when there are no structural breaks in the observation. Therefore, the hypothesis that the variance of both regressions are equal is rejected in the presence of structural break. To test whether the crisis affects the level of banking competition, two subsample periods are used. The first subsample includes a sample period from 2005–2008, and the second covers the post crisis periods (2009–2011).

Furthermore, to make the assumption of homoscedasticty and no autocrrelation more likely to hold, within transformation is used to estimate the parameters. In addition, year fixed effects are included in the regression to control for unobserved time effects and to make the assumption that the errors are not correlated across individuals more likely to hold. Standard errors are adjusted for within-group correlation clustered at the country level to address heteroscedasticity.

The Chow test of the regressions examined in the previous dummy variable based test section rejects the null hypothesis that there is no structural break after 2008 at the 5% level (Table 4.7). Therefore, the results of the test reconfirm those of the dummy variable based test in the previous section ("Dummy Variable Based Test"), which suggest that there is a structural change in bank competition following the financial crisis.

4.7.3. Alternative Measure of Profit

To examine the sensitivity of the main results with respect to the measure of profitability, ROA is replaced with ROE. ROE is defined as net income divided by average total book equity of the bank. Data on these variables are collected from Orbis Bank Focus. As with ROA, ROE is also winsorised at the top and bottom 1%.

The results based on ROE, presented in Table 4.8 are qualitatively similar to those based on ROA (Table 4.4). First, the results in Table 4.8 also support the second hypothesis that "*herding is desirable if the competition in the banking industry is low. Therefore, profit is negatively related to the degree of profit persistence conditional on herding and positively related to the degree of unconditional profit persistence.*" This inference, in particular, is supported by the negative and significant coefficients of *ROE_{t-1} x DGC_Leader_{t-1}*. Furthermore, the coefficients of *ROE_{t-1}* (i.e. the degree of unconditional profit persistence) are between 0.565 and 0.654, all of which are statistically significant. These estimates indicate that the competition in the banking industry is low. The observed size of the coefficients of *ROE_{t-1}* are also larger compared to those of *ROE_{t-1} x DGC_Leader_{t-1}*. Therefore, consistent with the estimates based on ROA, these findings suggest that excess profit from lower industry competition allows banks to compensate for reduced profit from herding.

The results in Table 4.8 also support the third hypothesis that "*the adverse effect of increased competition on profit is larger (smaller) for banks that are followed by (follow) other banks*". This is indicated by the statistically significant coefficients of *ROE_{t-1} x DGC_Leader_{t-1}* that are within the range of -0.022 and -0.020. However, those of *ROE_{t-1} x $DGC\_Follower_{t-1}$* are insignificant.

Similar to the evidence based on ROA, the findings based on ROE also support the ES hypothesis. This is indicated by the positive and significant coefficients of *$Market\ Share_{t-1}$*, whereas the coefficients of *HHI_{t-1}* remain insignificant across the models. The coefficients of *$LogTotalAssets_{t-1}$* (3.525) reported in column (3) of Table 4.8 are statistically significant only at 10%. This implies that larger banks to some extent gain higher profit due to scale economies. However, extremely large banks gain lower profit from higher total assets due to scale diseconomies. This is weakly indicated by the coefficients of *$LogTotalAssets\_sq_{t-1}$* (both -0.116) in columns (3)–(4) and statistically significant only at the 10%.

In addition to asset size, the results in columns (1)–(2) of Table 4.8 show that several other bank-specific characteristics also affect bank profit. More precisely, the coefficients of *$Equity\ to\ Total\ Assets_{t-1}$* are negative and statistically significant. The negative sign of the coefficients is consistent with the signalling hypothesis of Ross (1977) because the banks that anticipate higher profits may signal their expectation to the market by increasing their leverage. Furthermore, profit is related to liquidity. This is indicated by the negative coefficients of *Loans to Total Assets*$_{t-1}$, significant at the 5% and 10% levels. This suggests that banks with lower liquidity are more likely to incur losses to meet large unexpected liquidity needs. Moreover, the coefficients of *NPL to Total Assets*$_{t-1}$ are both negative and significant only at the 10% level. This provides some support to the argument of Biker and Hu (2002) that deterioration in loan quality reduces profit generated from lending.

4.7.4. Longer Sample Period for Identifying Herding

As explained in section 4.4.3 of this chapter, the Granger causality test in this study is run following Billio *et al.* (2012). The method requires banks to have at least 36 monthly stock returns within a 5-year period to enter the sample. Higher data frequency of stock return allows this study to estimate herding using a shorter time period compared to prior studies that use the Granger causality test on accounting data.[34]

To examine whether the result in section 4.6. is sensitive to the length of the sample period chosen, a longer sample period is used to identify herding and examine the effect of the alternative herding measure on the competition and profit of banks. In particular, a Granger causality test in this section is performed on a set of commercial

[34] For example, Jain and Gupta (1987) use a 6-year period of pooled semi-annual lending data in a panel of countries. Similarly, Barron and Valev (2000) use a 13-year period of semi-annual lending data

banks that have 120 data of monthly stock returns within a 10-year sample period to detect herding.[35]

As shown in Table 4.9, the 10-year herding measures, *DGC_Leader_10yr* and *DGC_Follower_10yr*, are both positively correlated with their respective baseline (3-to-5 year) herding measures, *DGC_Leader* and *DGC_Follower*. In particular, the correlation between the two leader measures, *DGC_Leader* and *DGC_Leader_10yr*, is 0.354 and that between the follower measures, *DGC_Follower* and *DGC_Follower_10yr*, is 0.336, both at the 1% level.

DGC_Leader_10yr is positively correlated with *Log Total Assets* and *Market Share,* both at the 1% level. In addition, *DGC_Follower_10yr* is negatively correlated with both variables each at the 1% and 5% significance levels. These correlations suggest banks that are followed by (follow) other banks have larger (smaller) asset size and market share. The findings are consistent with those reported in Table 4.3.

The results based on the 10-year herding measures (Table 4.10) are to some extent qualitatively similar to previous results using the 3-to-5 year herding measures (Table 4.4). The results support the second hypothesis that bank herding is desirable if competition in the banking industry is low. The coefficients of ROA_{t-1} *x* $DGC\_Leader\_10yr_{t-1}$ are negative and significant at the 5% and 10% levels (columns (1)–(4)). These estimates indicate that herding increases bank competition and reduces profit, especially for banks followed by other banks. The coefficients of ROA_{t-1} are between 0.617 and 0.812, and statistically significant at the 1% level across the models, suggesting that the level of competition in the banking industry is low. The size of the coefficient of ROA_{t-1} is also larger compared to those of ROA_{t-1} *x*

[35] For example, to detect herding between a pair of banks in 2018, data of monthly stock returns from 2009 to 2018 of the respective banks are used.

DGC_Leader_10yr$_{t-1}$ in columns (1)-(4). This indicates lower competition in the banking industry allows banks to generate excess profit to mitigate the lower profits from herding.

The results reported in columns (1)–(4) (Table 4.10) also support the third hypothesis. More precisely, the coefficients of ROA_{t-1} *x DGC_Leader*$_{t-1}$*_10yr* in columns (1)–(4) are between -0.011 and -0.005, statistically significant at the 5% and 10% levels. However, the coefficients of ROA_{t-1} *x DGC_Follower*$_{t-1}$*_10yr* are insignificant.

4.8. Conclusions

The key objective of this chapter was to examine the effect of herding on the competition and profit of banks. Three related hypotheses were proposed and tested, as explained in section 4.3.2 of this chapter. POP models were used to test the hypotheses and estimate the effect of herding on the competition and profit of banks. Bank profit was measured by both ROA and ROE, and herding was measured by bank-level degree of Granger causality, consistent with that used in the third chapter of this thesis ("Systemic Risk Implications of Bank Herding").

Bank profits were regressed on their own lagged values, the interaction between both the lagged profit and the herding measures, controlling for other known profit determinants. These include market structure, bank-specific characteristics and macroeconomic factors. All explanatory variables were lagged by one period. In addition, year fixed effects were included to control for unobserved time effects. System GMM was used to estimate the parameters and to control for time-invariant unobserved bank heterogeneity and simultaneity bias.

The empirical results show that the degree of profit persistence conditional on herding, measured by the coefficients of the interactions between herding and lagged profit, are negative. In addition, the coefficient of the lagged profit (i.e. the unconditional profit persistence) is above 0.5, suggesting a low level of competition in the banking industry. The magnitude of the coefficient of the unconditional profit persistence is also larger compared to that of profit persistence conditional on herding. This evidence rejects the first hypothesis but supports the second that herding is desirable because of weak competition in the banking industry.

The findings also support the third hypothesis that smaller banks have more incentive to herd and, consequently, the too-many-to-fail phenomenon affects small banks more than large banks. This is indicated by the lower degree of profit persistence conditional on herding when banks are followed by other banks compared to the opposite. The finding supports the theory of Acharya and Yorulmazer (2007) that small banks have more incentive to herd and, consequently, the too-many-to-fail affects small banks more than large banks. It is also consistent with related studies on bank competition and performance (Boot and Thakor, 2000; Stein, 2002; VanHoose, 2017), which find that larger banks are more exposed to the negative effect of increased competition on profit.

This chapter contributes to the literature on bank herding and bank competition by providing empirical evidence on bank competition and profit in the presence of herding. The findings of this study have several policy implications for regulators with a financial stability mandate. First, regulators can increase competition in the banking industry, i.e. by reducing entry barriers, to deter herding and therefore mitigate systemic risk. Higher competition would reduce the buffer to withstand lower profit margins from herding and hence reduce banks' incentives to herd.

Next, the findings highlight the importance for regulators to adopt macroprudential policy in association with microprudential policy, especially for countries that are proponents of market power-stability. More precisely, the market-power stability posits that market concentration and the resulting higher profits increase banks' charter value, thereby reducing excessive risk-taking. Nonetheless, this study shows that lower competition in the industry provides room for banks to herd, therefore increasing systemic risk.

Table 4.1
List of countries

This table presents the list of countries and the respective number of banks for each countries included to compute the DGC or herding measures. To compute the measure, countries are required to have at least five listed banks.

Country	# Banks	Country	# Banks
Australia	7	Malaysia	6
Austria	5	Montenegro	5
Bahrain	6	Morocco	6
Bangladesh	24	Nigeria	10
Bosnia and Herzegovina	9	North Macedonia	5
Brazil	13	Oman	6
Canada	10	Pakistan	20
Chile	7	Peru	6
China	27	Philippines	13
Colombia	7	Poland	10
Croatia	7	Qatar	6
Denmark	21	Russian Federation	15
Egypt	8	Saudi Arabia	8
Germany	10	Spain	6
Ghana	5	Sri Lanka	16
Greece	5	Switzerland	5
India	37	Syrian Arab Republic	11
Indonesia	38	Taiwan	11
Iraq	10	Thailand	9
Israel	9	Tunisia	10
Italy	16	Turkey	21
Japan	67	Ukraine	8
Jordan	14	United Arab Emirates	15
Kazakhstan	8	United States	74
Kenya	7	Venezuela	6
Kuwait	5	Viet Nam	10
Lebanon	6		

Table 4.2
Summary statistics

This table provides the summary statistics of bank profit and its determinants for the sample of cross-country publicly listed commercial banks. ROA (%) is defined as net income divided by average total assets, expressed in percentages. DGC-Leader and DGC-Follower are both the herding measures, expressed in percentages. HHI is the Herfindahl-Hirschman Index, which measures the country-level banking system concentration and is defined as the sum of the squared market share of all banks within a country. Bank-level market share is included to control for the spurious relationship between profit and market concentration, consistent with the Efficient Structure hypothesis. Log Total Assets is the natural logarithm of total assets (in thousands of USD). Equity/Total Assets (%) is the ratio equity to total assets. Loans/Total Assets (%) is the ratio of net loans to total assets. Non-interest Income (NII) to Total Operating Revenue (%) measures banks income diversification. Net Charge-Offs (NCO) to Loans and Non-Performing Loans (NPL) to Total Assets are included as substitute variables to control for the effect of bank loan risk on profit. GDP Growth (%) and Inflation (%) are each country's specific GDP growth and inflation rate, expressed in percentages.

Variable	N	Min	Q1	Mean	Median	Q3	Max	Std. Dev
Dependent Variable								
ROA (%)	3483	-9.015	0.462	1.046	0.969	1.516	8.961	1.605
Herding Measures								
DGC-Leader (%)	3483	0.000	0.000	9.419	5.882	14.286	80.000	11.994
DGC-Follower (%)	3483	0.000	0.000	9.314	5.556	14.286	86.957	12.157
Market Structure								
HHI	3481	0.058	176.784	1083.162	825.969	1558.047	5192.931	1019.646
Market Share (%)	3397	0.000	0.361	6.131	2.339	8.831	70.567	9.053
Bank-Specific Characteristics								
Log Total Assets	3402	9.045	14.366	15.875	15.936	17.418	22.120	2.231
Equity/Total Assets (%)	3402	-126.595	6.933	11.531	9.761	13.307	98.698	9.575
Loans/Total Assets (%)	3376	0.021	50.194	57.968	61.119	68.170	97.625	15.408
NII to Total Op. Rev (%)	3388	-220.911	21.764	32.959	30.240	40.080	439.029	22.123
NPL to Total Assets (%)	3101	0.000	0.879	3.713	1.944	3.831	70.526	6.152
NCO to Loans (%)	2863	-94.506	0.005	0.447	0.187	0.643	42.079	2.628
Macroeconomic Factors								
GDP Growth (%)	3483	-17.040	1.825	3.399	2.908	5.033	25.122	3.226
Inflation (%)	3483	-3.830	0.843	5.073	2.174	5.128	862.629	31.917

Table 4.3
Pairwise correlations

This table reports pairwise correlations between bank profit, the interactions between lagged profit and bank herding, market structure, bank-specific characteristics, and macroeconomic factors. In parentheses and brackets below the correlation are the corresponding p-values and the number of observations, respectively.

	ROA (%)	DGC_Leader_{t-1} (%)	$DGC\_Follower_{t-1}$ (%)	ROA x DGC_Leader_{t-1}	ROA x $DGC\_Follower_{t-1}$	HHI_{t-1}	Market $Share_{t-1}$ (%)
ROA (%)	1						
	[3483]						
DGC_Leader_{t-1} (%)	0.0581	1					
	(0.0006)						
	[3483]	[3483]					
$DGC\_Follower_{t-1}$ (%)	-0.0037	-0.1638	1				
	(0.8293)	(0.0000)					
	[3483]	[3483]	[3483]				
ROA x DGC_Leader_{t-1}	0.0796	0.3495	-0.0551	1			
	(0.0000)	(0.0000)	(0.0013)				
	[3401]	[3401]	[3401]	[3401]			
ROA x $DGC\_Follower_{t-1}$	0.1495	-0.0377	0.2622	0.3795	1		
	(0.0000)	(0.0280)	(0.0000)	(0.0000)			
	[3401]	[3401]	[3401]	[3401]	[3401]		
HHI_{t-1}	0.0665	0.0373	0.0324	0.0033	0.0124	1	
	(0.0001)	(0.0277)	(0.0559)	(0.8465)	(0.4715)		
	[3481]	[3481]	[3481]	[3400]	[3400]	[3481]	
Market $Share_{t-1}$ (%)	0.1028	0.0839	-0.0250	0.0667	0.0200	0.3736	1
	(0.0000)	(0.0000)	(0.1458)	(0.0001)	(0.2440)	(0.0000)	
	[3397]	[3397]	[3397]	[3396]	[3396]	[3397]	[3397]
Log Total $Assets_{t-1}$	-0.0339	0.0393	-0.0623	0.0023	-0.0215	0.2015	0.4980
	(0.0483)	(0.0218)	(0.0003)	(0.8931)	(0.2108)	(0.0000)	(0.0000)
	[3402]	[3402]	[3402]	[3401]	[3401]	[3401]	[3397]
Equity to Total $Assets_{t-1}$ (%)	0.1967	0.0215	0.0357	0.3270	0.2421	0.0518	-0.0633
	(0.0000)	(0.2094)	(0.0372)	(0.0000)	(0.0000)	(0.0025)	(0.0002)
	[3402]	[3402]	[3402]	[3401]	[3401]	[3401]	[3397]
Loans to Total $Assets_{t-1}$ (%)	-0.0800	-0.0691	-0.0391	-0.0766	-0.0942	0.0027	-0.0124
	(0.0000)	(0.0001)	(0.0233)	(0.0000)	(0.0000)	(0.8760)	(0.4721)
	[3376]	[3376]	[3376]	[3375]	[3375]	[3375]	[3371]
NII to Total Op. $Rev._{t-1}$ (%)	0.1488	0.0551	0.0032	0.0880	0.0750	0.1153	0.0621
	(0.0000)	(0.0013)	(0.8530)	(0.0000)	(0.0000)	(0.0000)	(0.0003)
	[3388]	[3388]	[3388]	[3388]	[3388]	[3387]	[3383]
NPL to Total $Assets_{t-1}$ (%)	-0.1150	-0.0001	0.0586	-0.0336	-0.1113	0.0925	-0.0337
	(0.0000)	(0.9934)	(0.0011)	(0.0613)	(0.0000)	(0.0000)	(0.0603)
	[3101]	[3101]	[3101]	[3101]	[3101]	[3100]	[3100]
NCO to $Loans_{t-1}$ (%)	-0.0146	0.0366	-0.0057	-0.0129	-0.0564	-0.0211	0.0016
	(0.4341)	(0.0503)	(0.7594)	(0.4892)	(0.0025)	(0.2600)	(0.9305)
	[2863]	[2863]	[2863]	[2863]	[2863]	[2862]	[2858]
GDP $Growth_{t-1}$ (%)	0.0183	0.0255	0.0273	0.0133	0.0356	-0.0737	0.0109
	(0.2813)	(0.1321)	(0.1067)	(0.4398)	(0.0381)	(0.0000)	(0.5250)
	[3483]	[3483]	[3483]	[3401]	[3401]	[3481]	[3397]
$Inflation_{t-1}$ (%)	0.0899	-0.0125	-0.0100	0.0046	0.0193	-0.0255	-0.0079
	(0.0000)	(0.4621)	(0.5539)	(0.7870)	(0.2612)	(0.1325)	(0.6440)
	[3483]	[3483]	[3483]	[3401]	[3401]	[3481]	[3397]

Table 4.3 *(continued)*

Pairwise correlations

	Log Total Assets$_{t-1}$	Equity to Total Assets$_{t-1}$ (%)	Loans to Total Assets$_{t-1}$ (%)	NII to Total Op. Rev.$_{t-1}$ (%)	NPL to Total Assets$_{t-1}$ (%)	NCO to Loans$_{t-1}$ (%)	GDP Growth$_{t-1}$ (%)	Inflation$_{t-1}$ (%)
Log Total Assets$_{t-1}$	1							
	[3402]							
Equity to Total Assets$_{t-1}$ (%)	-0.3350	1						
	(0.0000)							
	[3402]	[3402]						
Loans to Total Assets$_{t-1}$ (%)	0.0338	-0.2146	1					
	(0.0495)	(0.0000)						
	[3376]	[3376]	[3376]					
NII to Total Op. Rev.$_{t-1}$ (%)	-0.0038	0.2883	-0.3111	1				
	(0.8269)	(0.0000)	(0.0000)					
	[3388]	[3388]	[3362]	[3388]				
NPL to Total Assets$_{t-1}$ (%)	-0.2069	0.1245	-0.0909	0.1861	1			
	(0.0000)	(0.0000)	(0.0000)	(0.0000)				
	[3101]	[3101]	[3100]	[3088]	[3101]			
NCO to Loans$_{t-1}$ (%)	0.0108	0.0438	-0.0009	-0.0032	0.0667	1		
	(0.5634)	(0.0192)	(0.9600)	(0.8627)	(0.0005)			
	[2863]	[2863]	[2863]	[2850]	[2723]	[2863]		
GDP Growth$_{t-1}$ (%)	0.1019	0.0879	0.0415	0.0196	-0.1449	0.0058	1	
	(0.0000)	(0.0000)	(0.0158)	(0.2549)	(0.0000)	(0.7547)		
	[3402]	[3402]	[3376]	[3388]	[3101]	[2863]	[3483]	
Inflation$_{t-1}$ (%)	-0.0991	-0.0413	-0.0754	-0.0120	-0.0186	0.0026	-0.2925	1
	(0.0000)	(0.0160)	(0.0000)	(0.4846)	(0.2994)	(0.8900)	(0.0000)	
	[3402]	[3402]	[3376]	[3388]	[3101]	[2863]	[3483]	[3483]

Table 4.4

Bank profit and herding relationship

This table reports regressions of bank profit, measured by ROA, and the interactions between herding and individual bank profit, controlling for market structure, bank-specific characteristics and country-specific macroeconomic conditions. Year fixed effects are included to control for unoberved time effects respectively. All explanatory variables are lagged by one period. Two-step system GMM with Windermeijer correction is used for all regressions. Standard errors, reported between parentheses, are clustered at the country level. ***,**, and * denote statistical significance at the 1%, 5% and 10% level respectively. The following diagnostic are reported: (1) The Arellano-bond tests for second order serial correlation in the residuals and (2) The Hansen test for over identification restriction, for which the null hypothesis is that the instruments are exogenous.

	ROA			
	(1)	(2)	(3)	(4)
Profit Persistence				
ROA_{t-1}	0.609***	0.597***	0.682***	0.670***
	(0.167)	(0.169)	(0.193)	(0.191)
Interaction Variables				
ROA_{t-1} x DGC_Leader_{t-1}	-0.017***	-0.018***	-0.047***	-0.047***
	(0.004)	(0.003)	(0.013)	(0.013)
ROA_{t-1} x $DGC\_Follower_{t-1}$	-0.005*	-0.006**	0.003	0.002
	(0.003)	(0.003)	(0.006)	(0.006)
Control Variables				
Market Structure				
HHI_{t-1}	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Market $Share_{t-1}$ (%)	0.020***	0.020***	0.025***	0.024***
	(0.006)	(0.006)	(0.008)	(0.008)
Bank-Specific Characteristics				
$LogTotalAssets_{t-1}$	0.231	0.369	0.715**	0.743**
	(0.229)	(0.233)	(0.309)	(0.317)
$LogTotalAssets\_sq_{t-1}$	-0.010	-0.013*	-0.023**	-0.024**
	(0.007)	(0.007)	(0.009)	(0.010)
Equity to Total $Assets_{t-1}$ (%)	-0.005	0.006	0.008	0.012
	(0.018)	(0.021)	(0.021)	(0.021)
Loans to Total $Assets_{t-1}$ (%)	-0.004	-0.004	-0.006	-0.006
	(0.003)	(0.003)	(0.004)	(0.004)
NII to Total Op. Rev_{t-1} (%)	0.007	0.006	0.001	0.001
	(0.006)	(0.006)	(0.004)	(0.004)
NPL to Total $Assets_{t-1}$ (%)	-0.018*	-0.018*		
	(0.010)	(0.010)		
NCO to $Loans_{t-1}$ (%)			-0.023	-0.025
			(0.035)	(0.035)
Macroeconomic Factors				
GDP $Growth_{t-1}$ (%)	0.011	0.019*	0.018	0.019*
	(0.008)	(0.010)	(0.011)	(0.011)
$Inflation_{t-1}$ (%)		0.003		0.003
		(0.002)		(0.003)
Number of Observations	3,086	3,086	2,845	2,845
AR(2) p_value	0.313	0.258	0.295	0.285
Hansen p_value	0.287	0.142	0.154	0.174
Year fixed effects	Yes	Yes	Yes	Yes

Table 4.5
Subsample analysis

This table reports the result using the subsample of non-U.S. and non-Western Europe countries. Two-step system GMM with Windermeijer correction is used for all regressions. Standard errors, reported between parentheses, are clustered at the country level. ***,**, and * denote statistical significance at the 1%, 5% and 10% level respectively. The following diagnostics are reported: (1) The Arellano-bond tests for second order serial correlation in the residuals and (2) The Hansen test for over identification restriction, for which the null hypothesis is that the instruments are exogenous.

	ROA (%)			
	(1)	(2)	(3)	(4)
Profit Persistence				
ROA_{t-1} (%)	0.593***	0.594***	0.683***	0.664***
	(0.180)	(0.171)	(0.210)	(0.206)
Interaction Variables				
ROA_{t-1} x DGC_Leader_{t-1}	-0.019***	-0.020***	-0.040***	-0.040***
	(0.003)	(0.003)	(0.013)	(0.013)
ROA_{t-1} x $DGC\_Follower_{t-1}$	-0.004	-0.005	0.004	0.004
	(0.008)	(0.008)	(0.004)	(0.004)
Control Variables				
Market Structure				
HHI_{t-1}	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Market $Share_{t-1}$ (%)	0.026***	0.026***	0.027***	0.027***
	(0.007)	(0.007)	(0.009)	(0.009)
Bank-Specific Characteristics				
$LogTotalAssets_{t-1}$	-0.161	0.148	0.127	0.172
	(0.308)	(0.293)	(0.490)	(0.519)
$LogTotalAssets\_sq_{t-1}$	0.002	-0.006	-0.006	-0.007
	(0.009)	(0.008)	(0.014)	(0.015)
Equity to Total $Assets_{t-1}$ (%)	0.004	0.018	0.000	0.005
	(0.024)	(0.024)	(0.028)	(0.029)
Loans to Total $Assets_{t-1}$ (%)	-0.007***	-0.006**	-0.007	-0.007
	(0.003)	(0.002)	(0.004)	(0.004)
NII to Total Op. Rev_{t-1} (%)	0.000	0.000	0.004	0.004
	(0.004)	(0.004)	(0.005)	(0.005)
NPL to Total $Assets_{t-1}$ (%)	-0.016	-0.013		
	(0.015)	(0.015)		
NCO to $Loans_{t-1}$ (%)			-0.030	-0.029
			(0.037)	(0.035)
Macroeconomic Factors				
GDP $Growth_{t-1}$ (%)	0.002	0.013	0.007	0.007
	(0.009)	(0.010)	(0.010)	(0.010)
$Inflation_{t-1}$ (%)		0.005**		0.001
		(0.002)		(0.003)
Number of Observations	2,406	2,406	2,217	2,217
AR(2) p_value	0.237	0.211	0.511	0.499
Hansen p_value	0.136	0.198	0.298	0.307
Year fixed effects	Yes	Yes	Yes	Yes

Table 4.6

Financial crisis and structural change in bank competition

This table provides the result of the structural break test using dummy variables equal to 1 for periods after the 2008 Global Financial Crisis. Two-step system GMM with Windermeijer correction is used for all regressions. Standard errors, reported between parentheses, are clustered at the country level. ***,**, and * denote statistical significance at the 1%, 5%, and 10% level respectively. The following diagnostics are reported: (1) The Arellano-bond tests for second order serial correlation in the residuals and (2) The Hansen test for over identification restriction for which the null hypothesis is that the instruments are exogenous. **C**olumns (1)–(2) of the table present the results of whether there is a structural shift of competition in the banking industry (unconditional profit persistence) post crisis, measured by the interaction between lag profit and the dummy variable (ROA_post). Columns (3)–(4) of Table 4.6 present the results of whether there is a structural shift of competition among banks that herd (conditional profit persistence) post crisis, measured by the interactuion between ROA_post and the herding measures.

	ROA (%)			
	(1)	(2)	(3)	(4)
Profit Persistence				
ROA_{t-1} (%)	0.489***	0.465***	0.619***	0.564***
	(0.094)	(0.102)	(0.114)	(0.131)
ROA_post	0.223***	0.214**		
	(0.081)	(0.089)		
Interaction Variables				
ROA_{t-1} x DGC_Leader_{t-1}	-0.001	0.000	-0.026**	-0.025*
	(0.004)	(0.005)	(0.012)	(0.013)
ROA_post x DGC_Leader_{t-1}			0.032**	0.032**
			(0.014)	(0.015)
ROA_{t-1} x $DGC\_Follower_{t-1}$	0.007	0.007	-0.017	-0.015
	(0.005)	(0.005)	(0.015)	(0.015)
ROA_post x $DGC\_Follower_{t-1}$			0.024*	0.023*
			(0.013)	(0.013)
Control Variables				
Market Structure				
Market $Concentration_{t-1}$	0.002	0.001	0.002	0.002
	(0.001)	(0.001)	(0.002)	(0.002)
Bank-Specific Characteristics				
$LogTotalAssets_{t-1}$	0.091	0.103	0.134	0.130
	(0.106)	(0.106)	(0.103)	(0.101)
$LogTotalAssets\_sq_{t-1}$	-0.006	-0.006	-0.009	-0.008
	(0.006)	(0.006)	(0.075)	(0.079)
Equity to Total $Assets_{t-1}$ (%)	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Loans to Total $Assets_{t-1}$ (%)	-0.000**	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
NII to Total Op. Rev_{t-1} (%)	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
NPL to Total $Assets_{t-1}$ (%)	-0.001	-0.001	0.000	0.000
	(0.001)	(0.002)	(0.002)	(0.002)
Macroeconomic Factors				
GDP $Growth_{t-1}$ (%)	0.027***	0.020**	0.032***	0.022**
	(0.008)	(0.009)	(0.009)	(0.010)
$Inflation_{t-1}$ (%)		0.017*		0.025***
		(0.010)		(0.009)
Number of Observations	884	880	884	880
AR(2) p_value	0.817	0.830	0.158	0.116
Hansen p_value	0.344	0.255	0.383	0.372
Year fixed effects	Yes	Yes	Yes	Yes

Table 4.7
Chow test

This table reports the result of the Chow test, which is used to examine whether competition in the banking industry has declined following the 2008 crisis. $\hat{\varepsilon}_{FS}{}'\hat{\varepsilon}_{FS}$ denotes the sum of squared errors of the full sample regression; $\hat{\varepsilon}_1{}'\hat{\varepsilon}_1$ is the sum of squared errors of the 2005–2008 period regression and $\hat{\varepsilon}_2{}'\hat{\varepsilon}_2$ is the sum of squared errors of the post crisis period (2009–2011) regression. J denotes the number of restrictions or the number of parameters in the full sample regression; *df* denotes the degree of freedom. To make the assumption of homoscedasticty and no autocorrelation more likely to hold, within transformation is used to estimate the parameters. In addition, year fixed effects are included in the regression to control for unobserved time effects and to make the assumption that the errors are not correlated across individuals more likely to hold. Standard errors are adjusted for within-group correlation clustered at the country level to address heteroscedasticity. The null hypothesis of no structural break after 2008 is rejected when F_statistic > F_critical.

	ROA (%)	
	(1)	(2)
$\hat{\varepsilon}_{FS}{}'\hat{\varepsilon}_{FS}$	199	195
$\hat{\varepsilon}_1{}'\hat{\varepsilon}_1$	57	53
$\hat{\varepsilon}_2{}'\hat{\varepsilon}_2$	75	75
J	17	18
df	853	851
F_statistic (*J*, *df*)	25.51	25.06
F_critical value (*J*, *df*, 0 .05/2)	1.63	1.62

Table 4.8

Alternative measure of profit

This table presents the results using a different measure of bank performance, which is ROE, using the same method and other variables as those in the previous estimation (Table 4.4). Data on ROE are collected from Orbis Bank Focus. Two-step system GMM with Windermeijer correction is used for all regressions. Standard errors, reported between parentheses, are clustered at the country level. ***,**, and * denote statistical significance at the 1%, 5% and 10% level respectively. The following diagnostic are reported: (1) The Arellano-bond tests for second order serial correlation in the residuals and (2) The Hansen test for over identification restriction which the null hypothesis is that the instruments are exogenous.

	ROE			
	(1)	(2)	(3)	(4)
Profit Persistence				
ROE_{t-1}	0.586**	0.654***	0.571***	0.565***
	(0.253)	(0.220)	(0.191)	(0.193)
Interaction Variables				
ROE_{t-1} x DGC_Leader_{t-1}	-0.022*	-0.022*	-0.021**	-0.020*
	(0.012)	(0.012)	(0.009)	(0.011)
ROE_{t-1} x $DGC\_Follower_{t-1}$	-0.005	-0.005	0.001	0.000
	(0.005)	(0.005)	(0.005)	(0.005)
Control Variables				
Market Structure				
HHI_{t-1}	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Market $Share_{t-1}$ (%)	0.214***	0.201***	0.138**	0.142**
	(0.066)	(0.068)	(0.065)	(0.066)
Bank-Specific Characteristics				
$LogTotalAssets_{t-1}$	2.286	2.071	3.525*	3.501
	(1.729)	(1.904)	(2.125)	(2.261)
$LogTotalAssets\_sq_{t-1}$	-0.089	-0.083	-0.116*	-0.116*
	(0.054)	(0.058)	(0.067)	(0.070)
Equity to Total $Assets_{t-1}$ (%)	-0.288***	-0.294**	-0.214	-0.240
	(0.103)	(0.142)	(0.210)	(0.211)
Loans to Total $Assets_{t-1}$ (%)	-0.052**	-0.049*	-0.033	-0.036
	(0.025)	(0.026)	(0.027)	(0.028)
NII to Total Op. Rev_{t-1} (%)	0.027	0.025	-0.017	-0.017
	(0.026)	(0.027)	(0.025)	(0.025)
NPL to Total $Assets_{t-1}$ (%)	-0.200*	-0.172*		
	(0.113)	(0.101)		
NCO to $Loans_{t-1}$ (%)			-0.030	-0.011
			(0.180)	(0.169)
Macroeconomic Factors				
GDP $Growth_{t-1}$ (%)	0.116	0.133	0.086	0.078
	(0.089)	(0.097)	(0.084)	(0.088)
$Inflation_{t-1}$ (%)		0.003		-0.009
		(0.023)		(0.024)
Number of Observations	3,086	3,086	2,845	2,845
AR(2) p_value	0.400	0.422	0.592	0.591
Hansen p_value	0.308	0.296	0.126	0.122
Year fixed effects	Yes	Yes	Yes	Yes

Table 4.9
Pairwise correlations between the baseline herding measures, the 10-year herding measures, total assets and market share

	DGC_Leader (%)	DGC_Follower (%)	DGC_Leader_10yr (%)	DGC_Follower_10yr (%)	Log Total Assets	Market Share (%)
DGC_Leader (%)	1					
	[3483]					
DGC_Follower (%)	-0.1638	1				
	(0.0000)					
	[3483]	[3483]				
DGC_Leader_10yr (%)	0.3537	-0.1677	1			
	(0.0000)	(0.0000)				
	[2398]	[2398]	[2398]			
DGC_Follower_10yr (%)	-0.0949	0.3256	-0.2226	1		
	(0.0000)	(0.0000)	(0.0000)			
	[2398]	[2398]	[2398]	[2398]		
Log Total Assets	0.0393	-0.0623	0.1713	-0.0661	1	
	(0.0218)	(0.0003)	(0.0000)	(0.0013)		
	[3402]	[3402]	[2358]	[2358]	[3402]	
Market Share (%)	0.0839	-0.0250	0.1873	-0.0410	0.4980	1
	(0.0000)	(0.1458)	(0.0000)	(0.0463)	(0.0000)	
	[3397]	[3397]	[2358]	[2358]	[3397]	[3397]

In parentheses and brackets below the correlation are the corresponding p-values and the number of observations.

Table 4.10

Longer sample period for identifying herding

This table shows the result using the longer (10-year) sample period to identify herding. In particular, the Granger causality test is performed on a set of commercial banks that have 120 pieces of data of monthly stock returns within a 10-year observation period. Two-step system GMM with Windermeijer correction is used for all regressions. Standard errors, reported between parentheses, are clustered at the country level. ***,**, and * denote statistical significance at the 1%, 5% and 10% level respectively. The following diagnostics are reported: (1) The Arellano-bond tests for second order serial correlation in the residuals and (2) The Hansen test for over identification restriction, for which the null hypothesis is the instruments are exogenous.

	ROA (%)			
	(1)	(2)	(3)	(4)
Profit Persistence				
ROA_{t-1} (%)	0.635***	0.617***	0.812***	0.805***
	(0.120)	(0.158)	(0.143)	(0.144)
Interaction Variables				
ROA_{t-1} x DGC_Leader_{t-1}	-0.005*	-0.011*	-0.010**	-0.010**
	(0.003)	(0.006)	(0.005)	(0.005)
ROA_{t-1} x $DGC\_Follower_{t-1}$	-0.004	-0.004	-0.004	-0.003
	(0.003)	(0.004)	(0.003)	(0.003)
Control Variables				
Market Structure				
HHI_{t-1}	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Market $Share_{t-1}$ (%)	0.008*	0.014**	0.007**	0.007**
	(0.005)	(0.006)	(0.004)	(0.003)
Bank-Specific Characteristics				
$LogTotalAssets_{t-1}$	0.178	0.361**	0.180*	0.191*
	(0.144)	(0.173)	(0.104)	(0.103)
$LogTotalAssets\_sq_{t-1}$	-0.006	-0.012**	-0.005	-0.006*
	(0.005)	(0.006)	(0.003)	(0.003)
Equity to Total $Assets_{t-1}$ (%)	0.044**	0.038**	0.032**	0.032**
	(0.018)	(0.018)	(0.014)	(0.014)
Loans to Total $Assets_{t-1}$ (%)	-0.001	-0.002	-0.003*	-0.003*
	(0.002)	(0.002)	(0.001)	(0.001)
NII to Total Op. Rev_{t-1} (%)	0.008	0.008	0.000	0.000
	(0.006)	(0.006)	(0.002)	(0.002)
NPL to Total $Assets_{t-1}$ (%)	-0.023***	-0.028***		
	(0.008)	(0.008)		
NCO to $Loans_{t-1}$ (%)			0.085	0.085
			(0.066)	(0.066)
Macroeconomic Factors				
GDP $Growth_{t-1}$ (%)	0.008	0.007	0.003	0.001
	(0.007)	(0.007)	(0.010)	(0.010)
$Inflation_{t-1}$ (%)		-0.001		-0.004
		(0.007)		(0.006)
Number of Observations	2,286	2,286	2,154	2,154
AR(2) p_value	0.864	0.648	0.778	0.774
Hansen p_value	0.307	0.411	0.254	0.225
Year fixed effects	Yes	Yes	Yes	Yes

5. Conclusion

This thesis provides a rigorous empirical examination of the theory that banks herd to increase the likelihood of a collective bailout position should default occur (Acharya and Yorulmazer, 2007; Farhi and Tirole, 2012). To address this key research issue, three empirical research questions were developed and tested: 1) Do banks herd and do country-level factors explain herding consistent with the theoretical prediction? 2) If yes, does herding pose a systemic risk? and 3) How does herding affects the competition and profit of banks?

This empirical assessment is motivated by two reasons. First, the periodic occurrences of a large number of bank failures, such as the U.S. Savings and Loan Crisis of the 1980s, the Japanese Banking Crisis of the 1990s, the Asian Financial Crises in 1997–98, and the Global Financial Crisis in 2008, which raise questions regarding whether the causes of the problem have been fully identified and addressed. Acharya and Yorulmazer (2007) theoretically show that banks herd to increase the likelihood of a collective position should default occur and therefore, this herding behaviour could have systemic risk implications (Benoit *et al.*). However, systemic risk taking through herding has received less attention as a substantial literature has been devoted to the systemic risk of too-big-to-fail banks (Shleifer and Vishny, 2010; Laeven, Ratnovski and Tong, 2016).

Second, following the global financial crisis in 2008, several reforms have been introduced with the aim, among others, of mitigating systemic risk in the banking system. However, Benoit *et al.* (2017) argue that the new regulations, in particular

Basel III, do not explicitly deter bank herding. Moreover, they argue that the reforms may actually increase systemic risk by inducing commonality across banks.

Overall, the above discussion suggests that further research is necessary to fill the gap in the related literature and shed light on the systemic risk of bank herding. This study used cross-country commercial bank data from Orbis Bank Focus and covered samples ranging from 2012–2019. The key findings of this thesis are summarised below.

5.1. Bank Herding and its Determinants

The first empirical chapter ("Bank Herding and its Determinants") aims to identify whether banks do herd and the country-level factors that affect herding. Acharya and Yorulmazer (2007) argue that herding is observable in economies where shareholder protection laws are weak and fiscal costs to cover bank deposit insurance is large. Hence, cross-country herding should vary with relevant country-specific factors.

Following a Granger causality test on volatility-adjusted stock returns and the LSV method based on changes in Z-score, the findings indicate that banks do herd. Furthermore, the pairwise correlation between the herding measures, the Z-Score LSV and the DGC One-Way, is positive and significant at the 10% level. This suggests that both methods measure the same variable. In addition, according to the density distribution of both measures, the level of herding varies among countries. This indicates that herding is related to country-specific factors.

According to the distribution of the Z_i^2 for the Z-Score LSV, Russia in 2014 was identified as an outlier from the distribution.[36] The presence of the outlier suggests that the LSV method could be subject to spurious herding, as noted by Uchida and Nakagawa (2007). Several extreme low values of DGC were also observed. Spain and Austria are both identified as outliers in the measure.[37] The outliers suggest that the ability of banks to diversify their asset portfolio and the wide range of banking activities that are permitted may explain the reason for the low level of herding in these countries.

Furthermore, the herding measures were regressed on several country-level variables. Using least-squares dummy-variables and maximum likelihood to estimate the parameters for the model and controlling for macroeconomic variables and depth of credit information, the result suggests that herding is dependent on country-specific features.

Several country-level factors found to be significant in inducing herding include exposure to fiscal costs, banking sector characteristics, and regulatory and supervisory quality. Concerning exposure to fiscal costs, the results suggest that banks in countries with an explicit deposit insurance scheme are more inclined to herd. In addition, the extent of herding is more severe for banks operating in countries where the banking

[36] As explained in the respective empirical chapter, a possible explanation for the outlier is that in August 2014, the risks in the Russian banking sector increased significantly due to three factors: the imposition of international sanctions; the worsening economic outlook and the depreciation of the rouble (The Economist, 2014).

[37] As explained in the respective empirical chapter, the sample for Spain covers only the six largest commercial banks in the country and does not include saving banks (cajas de ahorros). The latter banks were the main source of the financial crisis that occurred in the country (Maudos and Vives, 2016) Two of the banks in the Spanish sample (Santander and BBVA) hold a well-diversified asset portfolio in geographical terms (Dewatripont, 2014). Austria has a universal banking system, allowing the banks to diversify their banking activities to a wider range of products and services (Knobl, 2018). Furthermore, Austrian banks activities are diversified geographically, with a significant market share in several Central, Eastern and Southeastern Europe countries (IMF, 2013).

sector plays an important role in the economy. This is measured by the size of the banking sector total assets and the size of non-financial corporation international debt outstanding to nominal GDP. The findings suggest that herding is more likely to occur in countries with exposure to large fiscal costs of deposit insurance. When fiscal costs are large, liquidation is not always costly compared to a bailout. This leads to time-inconsistency in bank closure policies or the too-many-to-fail problem (Acharya and Yorulmazer, 2007).

Regarding banking sector characteristics, this study shows that herding is more observable in countries with a concentrated or asymmetric banking sector. In such a banking sector, few large banks dominate the industry and the market share difference between the large banks and the small banks is large. Hence, large banks in such a banking sector are likely banks that are too-big-to-fail, and the failure of one of these banks is likely to cause severe impairment in the financial system (Laeven, Ratnovski and Tong, 2016). More precisely, when one of these large banks fail, the banking sector's capacity to acquire failed banks is significantly reduced. This in turn increases liquidation costs and the likelihood of bailouts. Therefore, small banks have a greater incentive to imitate large banks in an asymmetric banking sector. The result is consistent with the theory that the too-many-to-fail phenomenon affects small banks more than large banks.

The finding also supports the strategic substitute hypothesis (Perotti and Suarez, 2002). In a symmetric banking sector, banks have more of an incentive to differentiate themselves. This is because each bank has the same likelihood of purchasing the other bank at a discount and increasing its market share. Hence, banks are more likely to herd in an asymmetric banking sector compared to a symmetric one.

This chapter also shows that activity restrictions induce herding. Although larger banks are more likely to pursue a different strategy, regulations that restrict banking activity constrain the ability of larger banks to differentiate themselves. Hence, smaller banks are more likely to follow larger banks when banking activity is restricted in a country.

Furthermore, the result shows that herding is more prevalent in countries where the regulatory and supervisory quality of the banking sector is weak. The result is consistent with that of Brown and Dinç (2011), which shows that the government's decision to liquidate a bank depends on the financial health of the banking industry. Hence, herding is less likely observable in countries with a better regulatory and supervisory quality.

Although the effect of most of the country-level factors on herding are statistically significant, shareholder protection laws are not. A possible explanation for why weak shareholder protection laws and, in turn, greater inside ownership of banks are less relevant is that shareholders of banks with dispersed ownership also receive subsidies in the event their banks are bailed out. More precisely, during the 2008 Global Financial Crisis, most governments used hybrid securities, i.e. preferred shares, instead of common stock to limit the risk of taxpayer loss (King, 2009). This led to a lesser dilution of common shares. Accordingly, herding may occur in countries where shareholder protection laws are not necessarily weak. This supports the argument of Brown and Dinç (2011) that, given the evidence of regulatory forbearance amidst too-many-to-fail problems in emerging markets, similar cases may also appear in developed countries.

The findings contribute to the herding literature in several ways. First, the chapter provides an empirical evidence of the theoretical proposition that banks herd to increase the likelihood of a collective bailout position should default occur. Furthermore, this chapter contributes to the existing empirical literature by providing a cross-country study and investigating whether country-specific factors affect herding. Existing empirical studies are more geared towards single-country study. However, Acharya and Yorulmazer (2007) suggest that country-specific factors affect herding.

5.2. Systemic Risk Implications of Bank Herding

The second empirical chapter ("Systemic Risk Implications of Bank Herding") answers the second research question of whether herding poses a systemic risk. Although the fact that a set of banks have a collective bailout position should default occur is evident from the first empirical chapter ("Bank Herding and its Determinants"), they may not necessarily pose a systemic risk. This may occur because the herding is spurious or its impact on systemic risk is limited due to the introduction of several prudential regulations in 2011.

Evidence documented in this chapter suggests that herding does pose systemic risk through its interactions with individual bank vulnerabilities. Following Laeven, Ratnovski and Tong (2016), the latter variables were measured using several ratios: (a) equity to total assets; (b) deposits to total assets and (c) loans to total assets. Each of the ratios measure different aspects of individual bank vulnerabilities, namely: capital structure; funding structure and asset structure. The variables are subsequently interacted with bank-level herding measures.

Furthermore, systemic risk measures were regressed on the interaction terms, controlling for several factors. These factors comprise: bank-specific characteristics which includes individual bank vulnerabilities, financial safety nets and country-specific macroeconomic factors. Both ΔCoVaR (Adrian and Brunnermeier, 2016) and SRISK (Brownlees and Engle, 2017) were used as systemic risk measures in this study.

The results suggest that the relation between ΔCoVaR and the interaction of herding and individual bank vulnerabilities, especially funding structure and asset structure, are positive and statistically significant. There are two implications of the findings. First, herding amplifies the effect of individual bank vulnerabilities on systemic risk. This is consistent with several related studies that have argued that herding reinforces the propagation channels of systemic risk (Acharya and Yorulmazer, 2007; Farhi and Tirole, 2012; Benoit *et al.*, 2017). Next, the findings highlight the importance of considering bank interconnectedness in systemic risk analyses and policy recommendations to capture the overall dimensions of systemic risk.

Furthermore, the result shows that the relationship between ΔCoVaR and the interaction of capital structure and herding is not statistically significant. The finding suggests that the adoption of Basel III, which requires designated systemically important banks to hold additional capital buffer against risk weighted assets, may weaken the relationship between systemic risk and capital structure. More precisely, larger banks may have less incentive to take excessive credit risk and market risk,[38]

[38] As highlighted in the respective empirical chapter, several studies have found that G-SIBs and advanced economy banks have shied away from trading and more complex activities. The trend has lowered market risk from the pre-crisis level. The average risk weight on banks' assets has also declined, reflecting a shift in the composition of credit portfolios towards assets with lower risk weights (BIS, 2018; Caparusso *et al.*, 2019).

which are both subject to higher capital charge. This in turn reduces the negative externalities from the too-big-to-fail phenomenon.

In addition, the market may expect the regulation to reduce government support for too-big-to-fail (Bongini, Nieri and Pelagatti, 2015; Moenninghoff, Ongena and Wieandt, 2015). Hence, banks have less incentive to herd. Acharya and Yorulmazer (2007) argue that in an asymmetric banking system, smaller banks follow larger banks due to bailout subsidies. Accordingly, as the regulation is expected to reduce government support for too-big-to-fail banks, smaller banks may have less incentive to follow larger banks.

However, negative externalities from excessive liquidity risk and funding risk taking may not have been fully internalised through existing regulations. More precisely, although banks are required to hold liquid assets and limit their maturity mismatch, the regulations tend to focus more on mitigating individual bank risk. Hence, banks may hold excessive illiquid assets or wholesale funds compared to the socially optimal level, and increase their correlation due to bailout expectations (Farhi and Tirole, 2012).

Furthermore, when the alternative systemic risk measure, SRISK, was used the relationship between systemic risk and most of the interaction terms was found to be consistently significant. Nonetheless, the signs of the interaction terms are contrary to those when ΔCoVaR was used as the systemic risk measure. The difference in the finding may be attributed to the different aspects of systemic risk that the two measures emphasise. In particular, ΔCoVaR measures the VaR of the overall banking system as a result of a distress of an individual bank. However, SRISK measures the expected capital shortfall of an individual bank resulting from a severe systematic shock.

Analysing the interaction terms together with the related individual bank vulnerabilities suggests that banks with higher vulnerabilities, measured by higher (lower) loans (deposits) to total assets ratio, are more fragile to systematic shocks. Nonetheless, the effect of the shocks on capital shortfall, SRISK, is lower for banks that herd. The findings may suggest that SRISK captures the market expectations of bailout subsidies. In particular, when banks that herd increase their vulnerabilities to systematic shocks, the market expects a higher likelihood of joint failures and government bailouts. Accordingly, when banks vulnerabilities increase, the amount of capital shortfall, SRISK, for banks that herd is lower compared to that for other banks in the industry.

The findings are consistent with the theory that the likelihood of government bailouts induces herding (Acharya and Yorulmazer, 2007; Farhi and Tirole, 2012). The findings are also consistent with the argument of Laeven, Ratnovski and Tong (2016) that market values of bank equity may reflect market expectations of government support.

The overall findings contribute to both the herding literature and systemic risk literature in several ways. First, this chapter provides empirical evidence on systemic risk taking by banks through herding (Acharya and Yorulmazer, 2007; Farhi and Tirole, 2012). Therefore, this study fills the void in the existing literature on herding that tends to focus more on methods to detect the phenomenon.

Next, this chapter provides a contribution to the systemic risk literature by improving analyses on systemic risk determinants. More precisely, Benoit *et al.* (2017) show that there are two main strands of systemic risk literature. The first studies a specific propagation channel of systemic risk, and the second are those related to systemic risk measurements. Although the latter provide methods for measuring systemic risk, they do not commonly identify a particular channel of systemic risk and focus more on individual bank vulnerabilities as determinants (López-Espinosa *et al.*, 2012; Adrian and Brunnermeier, 2016). Therefore, this chapter improves existing systemic risk analyses by relating bank interconnectedness from herding with systemic risk measures.

5.3. The Effect of Herding on the Competition and Profit of Banks

The third empirical chapter ("The Effect of Herding on the Competition and Profit of Banks") seeks to explain how herding affects the competition and profit of banks. Acharya and Yorulmazer (2007) suggest that profit deterioration could countervail herding incentives in their theoretical model. However, several empirical studies have found evidence of bank herding (Barron and Valev, 2000; Uchida and Nakagawa, 2007).

A possible explanation to why banks continue to herd is that competition among banks that herd is weaker compared to the rest of the banking industry (Uchida and Nakagawa, 2007). Banks that herd could operate in a less competitive banking market and/or are able to minimise the competition by colluding to protect themselves from profit deterioration. Collusion in the banking sector is not an uncommon issue. Neven and Röller (1999) find evidence of collusive behaviour among banks in seven European nations from 1981–1989. Another possible explanation as to why banks may herd amidst the possibility of reduced profit is that competition in the banking industry is low. In particular, herding may increase competition and reduce profit when banks herd by providing loans to the same industries (Acharya and Yorulmazer, 2007).

Nonetheless, herding may still be desirable because weaker industry competition allows banks to generate excess profit and compensate for the profit erosion caused by herding (Acharya and Yorulmazer, 2008).

This chapter used POP models to examine the effect of herding on bank competition and profit. Proponents of POP models argue that when competition is low, high profits can persist for longer and profits converge slowly to their long-run equilibrium (Mueller, 1977). The speed at which competition affects excess profit in the short-run is measured by the degree of first-order autocorrelation in time series profit data. Accordingly, when competition among banks that herd is weaker, profit is positively related to the interaction between the first lag of profit and the bank-level herding measures. In other words, profit persistence for banks that herd is higher. However, when herding increases competition, profit persistence for banks that herd is lower.

The results show some evidence of a higher level of competition among the banks that herd compared to rest of the industry. This is indicated by the negative and statistically significant relationship between bank profit, measured by ROA and ROE, and profit persistence conditional on bank herding. However, herding is desirable when competition in the banking industry is low. This is indicated by the coefficients of the unconditional one-year lagged profit, which are close to 1. In addition, the size of the coefficient of the measure is higher compared to that of the profit persistence conditional on herding. This suggests that lower competition in the banking industry allows banks to exploit larger economic rent to compensate for the lower profit from herding (Acharya and Yorulmazer, 2008).

In addition to the above key result, the evidence in this chapter shows that the adverse impact of herding on competition and profit is larger (lower) for banks that are followed by (follow) other banks. The result is consistent with the theory that small banks have more incentive to herd and, consequently, too-many-to-fail affects small banks more than large banks (Acharya and Yorulmazer, 2007).

The finding also supports the related hypotheses on bank competition and performance. The dominant-bank hypothesis posits that large dominant banks may engage in price competition to maintain their market share (VanHoose, 2017). They may also depend more on transaction lending (Stein, 2002; Carter, McNulty and Verbrugge, 2004), therefore, exposing them to the larger effect of increased competition (Boot and Thakor, 2000). However, smaller banks that herd may engage in relationship lending to avoid direct competition with larger banks, which the former imitate. This allows smaller banks to extract informational rent from their borrowers and partially insulate themselves from pure price competition (Boot and Thakor, 2000; Elsas, 2005).

The findings contribute to both the literature on herding and the literature on bank competition and performance. In particular, this chapter provides an empirical investigation of how herding affects competition and the profit of banks. Several related empirical studies exist. Nonetheless, they focus more on either detecting herding or testing hypotheses related to bank conduct and performance.

5.4. Implications of Findings and Recommendations for Future Research

5.4.1. Implications of Findings

The results of this thesis have several policy implications. First, the findings highlight the importance of regulators setting up system-wide monitoring of banking risk. A system-wide perspective would enable regulators to identify systemic-risk that may arise due to direct and/or indirect correlation among banks. The first empirical chapter ("Bank Herding and its Determinants") finds evidence that banks herd to increase the likelihood of a collective bailout position should default occur. In addition, the second empirical chapter ("Systemic Risk Implications of Bank Herding") finds evidence that herding poses a systemic risk.

Next, there is still room for regulatory improvements, although regulatory reforms have been introduced following the global financial crisis. The second empirical chapter ("Systemic Risk Implications of Bank Herding") shows that the relationship between systemic risk and most of the interaction terms between individual bank vulnerabilities and herding is significant. These vulnerabilities are related to bank funding structure and asset structure. Accordingly, regulators could mitigate the effect of herding on systemic risk by relating liquidity standards with cross-sectional systemic risk.

Finally, the findings suggest the possibility of using other policy measures to deter herding and mitigating systemic risk build-up as a result of the behaviour. In particular, the first empirical chapter ("Bank Herding and its Determinants") finds that banks in countries with an explicit deposit insurance scheme are more inclined to herd. Furthermore, herding is more likely to occur when the role of the banking sector in an economy is significant. This highlights the importance of reducing exposure to the high fiscal costs that may arise from deposit insurance. A possible method to achieve this is by diversifying the source of financing in bank-centric economies through financial deepening initiatives.

In addition, regulators can use competition policy to deter herding, with the aim of increasing competition in the banking industry. The third empirical chapter ("The Effect of Herding on the Competition and Profit of Banks") shows that the level of competition for banks that herd is higher compared to the industry. Nonetheless, herding is desirable if the competition in the banking industry is low. Higher profit from lower competition in the industry allows banks to compensate for profit erosion due to herding. Accordingly, regulators could deter herding by increasing competition in the banking industry. The result also highlights the importance for countries that are proponents of the market power-stability of adopting macroprudential policy in association with microprudential policy.

5.4.2. Recommendations for Future Research

As argued in the second empirical chapter ("Systemic Risk Implications of Bank Herding"), empirical studies should account for bank interconnectedness in addition to individual bank vulnerabilities when estimating systemic risk determinants. The result in the respective chapter shows that most of the interactions between individual bank vulnerabilities and herding are statistically significant in explaining systemic risk variation across banks. The finding highlights the importance of considering bank interconnectedness to improve systemic risk analyses and related policy recommendations.

Future empirical studies on systemic risk determinants should consistently incorporate other forms of bank interconnectedness. These may include interbank exposures that may arise from money market, derivatives and payment system transactions among banks. These studies should be supported by improvements in data availability. As commonly suggested, granular data on bilateral interbank exposure are often unavailable publicly (Upper, 2011; Battiston and Martinez-Jaramillo, 2018).

In addition, as evident in the third empirical chapter ("The Effect of Herding on the Competition and Profit of Banks"), herding affects the competition and profit of banks. Prior studies on the relation between bank competition and performance have not considered herding as a possible explanatory factor. The majority of empirical studies on bank competition and performance are aimed at testing the SCP hypothesis, which posits that market structure influences banks' competition and performance (profitability) (Hannan, 1991). These studies use market structure variables, such as concentration ratios, in addition to several bank-specific and macroeconomic factors to explain profit variation across banks (Athanasoglou, Brissimis and Delis, 2008; Mirzaei, Moore and Liu, 2013; McMillan and McMillan, 2016). The finding in the the third empirical chapter ("The Effect of Herding on the Competition and Profit of Banks") suggests that future research may benefit from looking beyond the current explanatory variables for explanations of variation in bank profitability.

References

Acharya, V.V. (2009) 'A theory of systemic risk and design of prudential bank regulation'. *Journal of Financial Stability,* 5 (3), pp. 224-255.

Acharya, V.V., Engle, R. and Richardson, M. (2012) 'Capital shortfall: a new approach to ranking and regulating systemic risks'. *American Economic Review,* 102 (3), pp. 59-64.

Acharya, V.V., Pedersen, L.H., Philippon, T., and Richardson, M. (2017) 'Measuring systemic risk'. *The Review of Financial Studies,* 30 (1), pp. 2-47.

Acharya, V.V., Mehran, H. and Thakor, A.V. (2016) 'Caught between Scylla and Charybdis? regulating bank leverage when there is rent seeking and risk shifting'. *The Review of Corporate Finance Studies,* 5 (1), pp. 36-75.

Acharya, V.V. and Yorulmazer, T. (2007) 'Too many to fail—an analysis of time-inconsistency in bank closure policies'. *Journal of Financial Intermediation,* 16, pp. 1-31.

Acharya, V.V. and Yorulmazer, T. (2008) 'Information contagion and bank herding'. *Journal of Money, Credit and Banking,* 40 (1), pp. 215-231.

Adams, Z., Füss, R. and Gropp, R. (2014) 'Spillover effects among financial institutions: a state-dependent sensitivity value-at-risk approach'. *Journal of Financial and Quantitative Analysis,* 49 (3), pp. 575-598.

Adrian, T. and Brunnermeier, M.K. (2016) 'CoVaR'. *American Economic Review,* 106 (7), pp. 1705-1741.

Adrian, T. and Shin, H.S. (2014) 'Procyclical leverage and value-at-risk'. *The Review of Financial Studies,* 27 (2), pp. 373-403.

Aghion, P., Bolton, P. and Dewatripont, M. (2000) 'Contagious bank failures in a free banking system'. *European Economic Review,* 44 (4), pp. 713-718.

Agur, I. (2014) 'Bank risk within and across equilibria'. *Journal of Banking and Finance,* 48, pp. 322-333.

Aharony, J. and Swary, I. (1996) 'Additional evidence on the information-based contagion effects of bank failures'. *Journal of Banking and Finance,* 20 (1), pp. 57-69.

Ahnert, T. and Georg, C.-P. (2018) 'Information contagion and systemic risk'. *Journal of Financial Stability,* 35, pp. 159-171.

Albertazzi, U. and Gambacorta, L. (2009) 'Bank profitability and the business cycle'. *Journal of Financial Stability,* 5 (4), pp. 393-409.

Allen, F., Babus, A. and Carletti, E. (2012) 'Asset commonality, debt maturity and systemic risk'. *Journal of Financial Economics*, 104 (3), pp. 519.

Allen, F. and Carletti, E. (2013) 'What is systemic risk?'. *Journal of Money, Credit, and Banking,* 45 (1), pp. 121-127.

Allen, F. and Gale, D. (2000) 'Financial contagion'. *Journal of Political Economy,* 108 (1), pp. 1-33.

Altunbaş, Y., Gardener, E.P.M., Molyneux, P., and Moore, B. (2001) 'Efficiency in European banking'. *European Economic Review,* 45 (10), pp. 1931-1955.

Amini, H. and Minca, A. (2012) 'Mathematical modeling of systemic risk', in Kranakis, E. (ed.) *Advances in network analysis and its applications.* Berlin: Springer, pp. 3-26.

Amidu, M. and Harvey, S.K. (2016) 'The persistence of profits of banks in Africa'. *Review of Quantitative Finance and Accounting,* 47 (1), pp. 83-108.

Anginer, D., Demirguc-Kunt, A. and Zhu, M. (2014a) 'How does competition affect bank systemic risk?'. *Journal of Financial Intermediation,* 23 (1), pp. 1-26.

Anginer, D., Demirguc-Kunt, A. and Zhu, M. (2014b) 'How does deposit insurance affect bank risk? Evidence from the recent crisis'. *Journal of Banking and Finance,* 48, pp. 312-321.

Arellano, M. and Bover, O. (1995) 'Another look at the instrumental variable estimation of error-components models'. *Journal of Econometrics,* 68 (1), pp. 29-51.

Athanasoglou, P.P., Brissimis, S.N. and Delis, M.D. (2008) 'Bank- specific, industry-specific and macroeconomic determinants of bank profitability'. *Journal of International Financial Markets, Institutions and Money,* 18 (2), pp. 121-136.

Avery, C. and Zemsky, P. (1998) 'Multidimensional uncertainty and herd behavior in finacial markets'. *The American Economic Review,* 88 (4), pp. 724-748.

Banerjee, A. (1992) 'A simple model of herd behavior'. *The Quarterly Journal of Economics,* 108 (3), pp. 797-817.

Bank for International Settlements (2010). *Macroprudential instruments and frameworks: a stocking of issues and experiences*. CGFS papers no.38.

Bank for International Settlements (2018). *Structural changes in banking after the crisis*. CGFS papers no.60.

Barbosa, K., de Paula Rocha, B. and Salazar, F. (2015) 'Assessing competition in the banking industry: A multi- product approach'. *Journal of Banking and Finance,* 50 (C), pp. 340-362.

Barron, J.M. and Valev, N.T. (2000) 'International lending by U.S. banks'. *Journal of Money, Credit and Banking,* 32 (3), pp. 357-381.

Barth, J.R., Caprio, G. and Levine, R. (2013) 'Bank regulation and supervision in 180 countries from 1999 to 2011'. *Journal of Financial Economic Policy,* 5 (2), pp. 111-219.

Basel Committee on Banking Supervision. (2010). *An assessment of the long-term economic impact of stronger capital and liquidity requirements*. Report.

Basel Committee on Banking Supervision. (2011). *Basel III: A global regulatory framework for more resilient banks and banking systems*. Report.

Battiston, S. and Martinez-Jaramillo, S. (2018) 'Financial networks and stress testing: Challenges and new research avenues for systemic risk analysis and financial stability implications'. *Journal of Financial Stability,* 35, pp. 6-16.

Baum, C.F. (2006) *An introduction to modern econometrics using Stata.* College Station, Tex.: Stata Press.

Baum, C., Schaffer, M. and Stillman, S. (2002) 'Instrumental variables and GMM: estimation and testing'. *IDEAS Working Paper Series from RePEc*.

Baum, C., Schaffer, M. and Stillman, S. (2007) 'Enhanced routines for instrumental variables/GMM estimation and testing'. *IDEAS Working Paper Series from RePEc*.

Beck, T., De Jonghe, O. and Schepens, G. (2012) 'Bank competition and stability: cross-country heterogeneity'. *Journal of Financial Intermediation,* 22, pp. 218-244.

Benoit, S., Colliard, J.-E., Hurlin, C., and Pérignon, C. (2017) 'Where the risks lie: a survey on systemic risk'. *Review of Finance,* 21 (1), pp. 109-152.

Berger, A.N. (1995a) 'The profit-structure relationship in banking--tests of market-power and efficient-structure hypotheses'. *Journal of Money, Credit and Banking,* 27 (2), pp. 404-431.

Berger, A.N. (1995b) 'The relationship between capital and earnings on banking'. *Journal of Money, Credit and Banking,* 27 (2), pp. 432-456.

Berger, A.N. and Black, L.K. (2011) 'Bank size, lending technologies, and small business finance'. *Journal of Banking and Finance,* 35 (3), pp. 724-735.

Berger, A.N. and Bouwman, C.H.S. (2013) 'How does capital affect bank performance during financial crises?'. *Journal of Financial Economics,* 109 (1), pp. 146-176.

Berger, A.N., Hasan, I. and Klapper, L.F. (2004) 'Further evidence on the link between finance and growth: an international analysis of community banking and economic performance'. *Journal of Financial Services Research,* 25 (2/3), pp. 169-202.

Berger, A.N. and Humphrey, D.B. (1997) 'Efficiency of financial institutions: International survey and directions for future research'. *European Journal of Operational Research*, 98 (2), pp. 175-212.

Berger, A.N., Klapper, L. and Turk-Ariss, R. (2009) 'Bank competition and financial stability'. *Journal of Financial Services Research,* 35 (2), pp. 99-118.

Berger, A.N. and Udell, G.F. (2002) 'Small business credit availability and relationship lending: the importance of bank organisational structure'. *Economic Journal,* 112 (477), pp. F32-F53.

Berger, A.N. and Udell, G.F. (2004) 'The institutional memory hypothesis and the procyclicality of bank lending behavior'. *Journal of Financial Intermediation,* 13 (4), pp. 458-495.

Besanko, D. and Kanatas, G. (1996) 'The regulation of bank capital: do capital standards promote bank safety?'. *Journal of Financial Intermediation,* 5 (2), pp. 160-183.

Bharath, S.T. and Shumway, T. (2008) 'Forecasting default with the Merton Distance to Default model'. *The Review of Financial Studies*, 21 (3), pp. 1339-1369.

Bikhchandani, S., Hirshleifer, D. and Welch, I. (1992) 'A theory of fads, fashion, custom, and cultural change as informational cascades'. *Journal of Political Economy,* 100 (5), pp. 992-1026.

Bikhchandani, S., Hirshleifer, D. and Welch, I. (1998) 'Learning from the behavior of others: conformity, fads, and informational cascades'. *Journal of Economic Perspectives*, 12 (3), pp. 151-170.

Bikhchandani, S. and Sharma, S. (2000) *Herd behavior in financial markets: A review*. IMF Working Paper.

Bikker, J. and Hu, H. (2002) 'Cyclical patterns in profits, provisioning and lending of banks and procyclicality of the new Basel capital requirements'. *Banca Nazionale Del Lavoro Quarterly Review,* 55 (221), pp. 143-175.

Billio, Getmansky, Lo, and Pelizzon (2012) 'Econometric measures of connectedness and systemic risk in the finance and insurance sectors'. *Journal of Financial Economics,* 104 (3), pp. 535-559.

Black, L.K. and Hazelwood, L.N. (2013) 'The effect of TARP on bank risk-taking'. *Journal of Financial Stability,* 9 (4), pp. 790-803.

Blundell, R. and Bond, S. (1998) 'Initial conditions and moment restrictions in dynamic panel data models'. *Journal of Econometrics,* 87 (1), pp. 115-143.

Boffelli, S. (2016) *Financial econometrics using Stata.* College Station, Tex.: Stata Press.

Bongini, P., Nieri, L. and Pelagatti, M. (2015) 'The importance of being systemically important financial institutions'. *Journal of Banking and Finance*, 50, pp. 562-574.

Boot, A.W.A. (2000) 'Relationship banking: what do we know?'. *Journal of Financial Intermediation,* 9 (1), pp. 7-25.

Boot, A.W.A. and Ratnovski, L. (2016) 'Banking and trading'. *Review of Finance,* 20 (6), pp. 2219-2246.

Boot, A.W.A. and Thakor, A.V. (2000) 'Can relationship banking survive competition?'. *Journal of Finance,* 55 (2), pp. 679-713.

Brown, C.O. and Dinç, I.S. (2011) 'Too many to fail? evidence of regulatory forbearance when the banking sector is weak'. *The Review of Financial Studies,* 24 (4), pp. 1378-1405.

Brownlees, C. and Engle, R.F. (2017) 'SRISK: a conditional capital shortfall measure of systemic risk'. *The Review of Financial Studies*, 30 (1), pp. 48-79.

Buckley and Olearchyk (2017). `Valeria Gontareva: reforming Ukraine's banking system`. *Financial Times*, 27 March.

Caballero, R.J. and Simsek, A. (2013) 'Fire sales in a model of complexity'. *Journal of Finance,* 68 (6), pp. 2549-2587.

Cai, J., Eidam, F., Saunders, A., and Steffen, S. (2018) 'Syndication, interconnectedness, and systemic risk'. *Journal of Financial Stability,* 34, pp. 105-120.

Calem, P. and Rob, R. (1999) 'The impact of capital-based regulation on bank risk-taking'. *Journal of Financial Intermediation,* 8 (4), pp. 317-352.

Calomiris, C.W. (1999) 'Building an incentive-compatible safety net'. *Journal of Banking and Finance,* 23 (10), pp. 1499-1519.

Caparusso, J., Chen, Y., Dattels, P., Goel, R., and Hiebert, P. (2019) *Post-crisis changes in global bank business models: A new taxonomy*. IMF Working Paper.

Caprio, G., Laeven, L. and Levine, R. (2007) 'Governance and bank valuation'. *Journal of Financial Intermediation,* 16 (4), pp. 584-617.

Carter, D.A., McNulty, J.E. and Verbrugge, J.A. (2004) 'Do small banks have an advantage in lending? an examination of risk-adjusted yields on business loans at large and small banks'. *Journal of Financial Services Research,* 25 (2/3), pp. 233-252.

Chang A., Chaudhuri S., and Jayaratne J. (1997). 'Rational herding and the spatial clustering of bank branches: an empirical analysis'. *Federal Reserve Bank of New York*, Research Paper No.9724, pp. 1-34.

Chang, M.-H. (1991) 'The effects of product differentiation on collusive pricing'. *International Journal of Industrial Organization,* 9 (3), pp. 453-469.

Chari, V.V. and Jagannathan, R. (1988) 'Banking panics, information, and rational expectations equilibrium'. *Journal of Finance,* 43 (3), pp. 749-761.

Chronopoulos, D.K., Liu, H., McMillan, F.J., and Wilson, J.O.S. (2015) 'The dynamics of US bank profitability'. *The European Journal of Finance,* 21 (5), pp. 426-443.

Chen, W., Hribar, P. and Melessa, S. (2018) 'Incorrect inferences when using residuals as dependent variables'. *Journal of Accounting Research,* 56 (3), pp. 751-796.

Chen, Y. (1999) 'Banking panics: the role of the first- come, first- served rule and information externalities'. *Journal of Political Economy,* 107 (5), pp. 946-968.

Choi, N. and Skiba, H. (2015) 'Institutional herding in international markets'. *Journal of Banking and Finance,* 55, pp. 246-259.

Chow, G.C. (1960) 'Tests of equality between sets of coefficients in two linear regressions'. *Econometrica,* 28 (3), pp. 591-605.

Cifuentes, R., Ferrucci, G. and Shin, H.S. (2005) 'Liquidity risk and contagion'. *Journal of the European Economic Association,* 3 (2- 3), pp. 556-566.

Claessens, S. and Kose, M.A. (2013) *Financial crises: explanations, types, and implications*. IMF Working Papers.

Colombo, S. (2013) 'Product differentiation and collusion sustainability when collusion is costly'. *Marketing Science,* 32 (4), pp. 669-674.

Cordella, T. and Yeyati, E.L. (2002) 'Financial opening, deposit insurance, and risk in a model of banking competition'. *European Economic Review,* 46 (3), pp. 471-485.

Coval, J.D. and Thakor, A.V. (2005) 'Financial intermediation as a beliefs-bridge between optimists and pessimists'. *Journal of Financial Economics,* 75 (3), pp. 535-569.

Craig, S.G. and Hardee, P. (2007) 'The impact of bank consolidation on small business credit availability'. *Journal of Banking and Finance,* 31 (4), pp. 1237-1263.

Cyree, K.B. and Spurlin, W.P. (2012) 'The effects of big-bank presence on the profit efficiency of small banks in rural markets'. *Journal of Banking and Finance,* 36 (9), pp. 2593-2603.

Dasgupta, A. (2004) 'Financial contagion through capital connections: a model of the origin and spread of bank panics'. *Journal of the European Economic Association*, 2 (6), pp. 1049-1084.

De Bandt, O. and Hartmann, P. (2000) *Systemic risk: a survey*. ECB Working Papers.

De Juan, R. (2003) 'The independent submarkets model: an application to the Spanish retail banking market'. *International Journal of Industrial Organization,* 21 (10), pp. 1461-1487.

Degryse, H., Moshe, K. and Steven, O. (2009) *Microeconometrics of banking.* New York: Oxford University Press.

Dell'Ariccia, G., Detragiache, E. and Rajan, R. (2008) 'The real effect of banking crises'. *Journal of Financial Intermediation*, 17 (1), pp. 89-112.

Dell'Ariccia, G., Friedman, E. and Marquez, R. (1999) 'Adverse selection as a barrier to entry in the banking industry'. *The RAND Journal of Economics,* 30 (3), pp. 515-534.

Dell'Ariccia, G. and Ratnovski, L. (2019) 'Bailouts and systemic insurance'. *Journal of Banking and Finance,* 105, pp. 166-177.

Demsetz, H. (1973) 'Industry structure, market rivalry, and public policy'. *The Journal of Law and Economics,* 16 (1), pp. 1-9.

Devenow, A. and Welch, I. (1996) 'Rational herding in financial economics'. *European Economic Review,* 40 (3), pp. 603-615.

Dewatripont, M. (2014) 'European banking: bailout, bail-in and state aid control'. *International Journal of Industrial Organization,* 34, pp. 37-43.

DeYoung, R. and Rice, T. (2004) 'Noninterest income and financial performance at U.S. commercial banks'. *Financial Review,* 39 (1), pp. 101-127.

Diamond, D.W. and Dybvig, P.H. (1983) 'Bank runs, deposit insurance, and liquidity'. *Journal of Political Economy,* 91 (3), pp. 401-419.

Diamond, D.W. and Rajan, R.G. (2001) 'Liquidity risk, liquidity creation, and financial fragility: a theory of banking'. *Journal of Political Economy,* 109 (2), pp. 287-327.

Diamond, D.W. and Rajan, R.G. (2005) 'Liquidity shortages and banking crises'. *Journal of Finance,* 60 (2), pp. 615-647.

Duchin, R. and Sosyura, D. (2014) 'Safer ratios, riskier portfolios: Banks response to government aid'. *Journal of Financial Economics,* 113, pp. 1-28.

Elsas, R. (2005) 'Empirical determinants of relationship lending'. *Journal of Financial Intermediation,* 14, pp. 32-57.

Elsinger, H., Lehar, A. and Summer, M. (2006) 'Risk assessment for banking systems'. *Management Science,* 52 (9), pp. 1301-1314.

Elzinga, K.G. and Mills, D.E. (2011) 'The Lerner index of monopoly power: Origins and uses'. *American Economic Review,* 101 (3), pp. 558-564.

Engle, R., Jondeau, E. and Rockinger, M. (2015) 'Systemic risk in Europe'. *Review of Finance,* 19, pp. 145-190.

Farhi, E. and Tirole, J. (2012) 'Collective moral hazard, maturity mismatch, and systemic bailouts'. *American Economic Review,* 102 (1), pp. 60-93.

Flannery, M., Kwan, S. and Nimalendran, M. (2013) 'The 2007-2009 financial crisis and bank opaqueness'. *Journal of Financial Intermediation,* 22 (1), pp. 55-84.

Flannery, M.J. and Hankins, K.W. (2013) 'Estimating dynamic panel models in corporate finance'. *Journal of Corporate Finance,* 19, pp. 1-19.

Freckleton, R.P. (2002) 'On the misuse of residuals in ecology: regression of residuals vs. multiple regression'. *Journal of Animal Ecology,* 71 (3), pp. 542-545.

Forssbæck, J. and Shehzad, C.T. (2015) 'The conditional effects of market power on bank risk—cross-country evidence'. *Review of Finance,* 19, pp. 1997-2038.

Freixas, X. and Rochet, J.-C. (2008) *Microeconomics of banking.* 2nd edn. MA: MIT Press.

Fu, X., Lin, Y. and Molyneux, P. (2014) 'Bank competition and financial stability in Asia Pacific'. *Journal of Banking and Finance,* 38, pp. 64-77.

Furfine, C.H. (2003) 'Interbank exposures: quantifying the risk of contagion'. *Journal of Money, Credit and Banking,* 35 (1), pp. 111-128.

Ghosh, S. (2017) 'RBI moves to curb ' short- changing' of clients, price rigging'. *Economic Times,* 22 May.

Goddard, J., Liu, H., Molyneux, P., and Wilson, J.O.S. (2010) 'Do Bank Profits Converge?'. *European Financial Management,* 19 (2), pp. 345-365.

Goddard, J., Liu, H., Molyneux, P., and Wilson, J.O.S. (2011) 'The persistence of bank profit'. *Journal of Banking and Finance,* 35 (11), pp. 2881-2890.

Goddard, J. and Wilson, J.O.S. (2009) 'Competition in banking: A disequilibrium approach'. *Journal of Banking and Finance,* 33 (12), pp. 2282-2292.

Goldberg, L.G. and Rai, A. (1996) 'The structure-performance relationship for European banking'. *Journal of Banking and Finance,* 20 (4), pp. 745-771.

Goodhart, C.A.E. and Huang, H. (2005) 'The lender of last resort'. *Journal of Banking and Finance,* 29 (5), pp. 1059-1082.

Gorton, G. and Metrick, A. (2012) 'Securitized banking and the run on repo'. *Journal of Financial Economics*, 104 (3), pp. 425-451.

Granger, C. (1969) 'Investigating causal relations by econometric models and cross-spectral methods'. *Econometrica,* 37 (3), pp. 424-438.

Granovetter, M. (1983) 'The strength of weak ties: a network theory revisited'. *Sociological Theory,* 1, pp. 201-233.

Granovetter, M.S. (1973) 'The strength of weak ties'. *American Journal of Sociology,* 78 (6), pp. 1360-1380.

Greene, W.H. (2017) *Econometric analysis.* 8th edn. New York: Pearson.

Gropp, R., Vesala, J. and Vulpes, G. (2006) 'Equity and bond market signals as leading indicators of bank fragility'. *Journal of Money, Credit and Banking,* 38 (2), pp. 399-428.

Hannan, T.H. (1991) 'Foundations of the Structure-Conduct-Performance paradigm in banking'. *Journal of Money, Credit and Banking,* 23 (1), pp. 68-84.

Häckner, J. (1995) 'Endogenous product design in an infinitely repeated game'. *International Journal of Industrial Organization,* 13 (2), pp. 277-299.

Horváth, B.L. and Wagner, W. (2017) 'The disturbing interaction between countercyclical capital requirements and systemic risk'. *Review of Finance,* 21 (4), pp. 1485-1511.

Huang, R. and Ratnovski, L. (2011) 'The dark side of bank wholesale funding'. *Journal of Financial Intermediation,* 20 (2), pp. 248-263.

Huang, X., Zhou, H. and Zhu, H. (2009) 'A framework for assessing the systemic risk of major financial institutions'. *Journal of Banking and Finance*, 33 (11), pp. 2036-2049.

Ibragimov, R., Jaffee, D. and Walden, J. (2011) 'Diversification disasters'. *Journal of Financial Economics,* 99 (2), pp. 333-333.

Idier, J., Lamé, G. and Mésonnier, J.-S. (2014) 'How useful is the Marginal Expected Shortfall for the measurement of systemic exposure? A practical assessment'. *Journal of Banking and Finance,* 47 (1), pp. 134-146.

International Monetary Fund. (2013). *Austria: Financial Sector Stability Assessment*. IMF Country Report No. 13/283.

International Monetary Fund. (2015). *Navigating Monetary Policy Challenges and Managing Risks*. Global Financial Stability Report.

International Monetary Fund, Bank for International Settlements, and Financial Stability Board. (2009). *Guidance to assess the systemic importance of* *financial institutions, markets and instruments: Initial considerations*. Report to G20 Finance Ministers and Governors.

Jain, A.K. and Gupta, S. (1987) 'Some evidence on " herding" behavior of U. S. banks'. *Journal of Money, Credit and Banking,* 19 (1), pp. 78-89.

Kara, G. (2016) '*Bank capital regulations around the world: what explains the differences'*. The Federal Reserve Board.

King, M. (2009) 'Time to buy or just buying time? the market reaction to bank rescue packages'. *IDEAS Working Paper Series from RePEc*.

Knobl, Dr. Peter (2018) *Banking regulation in Austria: overview*. Available at: https://uk.practicallaw.thomsonreuters.com (Accessed: 6 June 2018).

Koetter, M., Kolari, J.W. and Spierdijk, L. (2012) 'Enjoying the quiet life under deregulation? Evidence from adjusted Lerner indices for U.S. banks.(Author abstract)'. *Review of Economics and Statistics,* 94 (2), pp. 462-480.

Koenker, R. and Bassett, G. (1978) 'Regression quantiles'. *Econometrica,* 46 (1), pp. 33-50.

Kowsmann, P. and Margot, P. (2018) 'Major banks suspected of collusion in bond-rigging probe'. *Wall Street Journal,* 20 December.

Krainer, J. and Lopez, J. (2004) 'Incorporating equity market information into supervisory monitoring models'. *Journal of Money, Credit and Banking,* 36 (6), pp. 1043-1067.

Kroszner, R.S. and Strahan, P.E. (1996) 'Regulatory incentives and the thrift crisis: Dividends, mutual-to-stock conversions, and financial distress'. *Journal of Finance,* 51 (4), pp. 1285-1319.

Laeven, L. and Levine, R. (2007) 'Is there a diversification discount in financial conglomerates?'. *Journal of Financial Economics,* 85 (2), pp. 331-367.

Laeven, L., Ratnovski, L. and Tong, H. (2016) 'Bank size, capital, and systemic risk: some international evidence'. *Journal of Banking and Finance,* 69, pp. S25-S34.

Lakonishok, J., Shleifer, A. and Vishny, R.W. (1992) 'The impact of institutional trading on stock prices'. *Journal of Financial Economics,* 32 (1), pp. 23-43.

Laux, C. and Rauter, T. (2017) 'Procyclicality of U.S. bank leverage'. *Journal of Accounting Research,* 55 (2), pp. 237-273.

Lehar, A. (2005) 'Measuring systemic risk: A risk management approach'. *Journal of Banking and Finance,* 29 (10), pp. 2577-2603.

Levy-Yeyati, E., Martínez Pería, M.S. and Schmukler, S.L. (2010) 'Depositor behavior under macroeconomic risk: evidence from bank runs in emerging economies'. *Journal of Money, Credit and Banking*, 42 (4), pp. 585-614.

López-Espinosa, Moreno, Rubia, and Valderrama (2012) 'Short-term wholesale funding and systemic risk: a global CoVaR approach'. *Journal of Banking and Finance*, 36, pp. 3150-3162.

Lotti, F. and Gobbi, G. (2004) 'Entry decisions and adverse selection: an empirical analysis of local credit markets.'. *Journal of Financial Services Research,* 26 (3), pp. 225-244.

Marquez, R. (2002) 'Competition, adverse selection, and information dispersion in the banking industry'. *The Review of Financial Studies,* 15 (3), pp. 901-926.

Maudos, J. and Vives, X. (eds.) (2016) *Banking in Spain.* London: Palgrave McMillan.

McMillan, D. and McMillan, F. (2016) 'US bank market structure: Evolving nature and implications'. *Journal of Financial Services Research,* 50 (2), pp. 187-210.

Mehran, H. and Thakor, A. (2011) 'Bank capital and value in the cross-section'. *The Review of Financial Studies*, 24 (4), pp. 1019-1067.

Merton, R.C. (1974) 'On the pricing of corporate debt: the risk structure of interest rates'. *Journal of Finance,* 29 (2), pp. 449-470.

Merton, R.C. (1977a) 'An analytic derivation of the cost of deposit insurance and loan guarantees'. *Journal of Banking and Finance,* 1, pp. 3-11.

Merton, R.C. (1977b) 'On the pricing of contingent claims and the Modigliani-Miller theorem'. *Journal of Financial Economics,* 5 (2), pp. 241-249.

Mertzanis, C. (2014) 'Complexity analysis and systemic risk in finance: some methodological issues', in Kalyagin, V.A., Pardalos, P.M. and Rassias, T.M. (eds.) *Network Models in Economics and Finance.* 2014 edn. Switzerland: Springer International Publishing, pp. 199-237.

Mirzaei, A., Moore, T. and Liu, G. (2013) 'Does market structure matter on banks' profitability and stability? Emerging vs. advanced economies'. *Journal of Banking and Finance,* 37 (8), pp. 2920-2937.

Moenninghoff, S.C., Ongena, S. and Wieandt, A. (2015) 'The perennial challenge to counter Too-Big-to-Fail in banking: Empirical evidence from the new international regulation dealing with Global Systemically Important Banks'. *Journal of Banking and Finance,* 61, pp. 221-236.

Molyneux, P. and Thornton, J. (1992) 'Determinants of European bank profitability: A note'. *Journal of Banking and Finance,* 16 (6), pp. 1173-1178.

Morck, R., Shleifer, A. and Vishny, R.W. (1988) 'Management ownership and market valuation: an empirical analysis'. *Journal of Financial Economics*, 20, pp. 293-315.

Mueller, D.C. (1977) 'The persistence of profits above the norm'. *Economica,* 44 (176), pp. 369-380.

Nakagawa, R. and Uchida, H. (2011) 'Herd behaviour by Japanese banks after financial deregulation'. *Economica,* 78 (312), pp. 618-636.

Neven, D. and Röller, L.-H. (1999) 'An aggregate structural model of competition in the European banking industry'. *International Journal of Industrial Organization,* 17 (7), pp. 1059-1074.

Nickell, S. (1981) 'Biases in dynamic models with fixed effects'. *Econometrica,* 49 (6), pp. 1417-1426.

Nier, Yang, Yorulmazer, and Alentorn (2007) 'Network models and financial stability'. *Journal of Economic Dynamics and Control,* 31 (6), pp. 2033-2060.

Oesterreichische Nationalbank. (2017) *Financial Stability Report.* Vienna.

Ongena, S. and Smith, D.C. (2001) 'The duration of bank relationships'. *Journal of Financial Economics,* 61 (3), pp. 449-475.

Panzar, J. and Rosse, J. (1987) 'Testing for ' monopoly' equilibrium'. *Journal of Industrial Economics,* 35, 443-456.

Peltzman, S. (1977) 'The gains and losses from industrial concentration'. *The Journal of Law and Economics,* 20 (2), pp. 229-263.

Perotti, E. and Suarez, J. (2002) 'Last bank standing: what do I gain if you fail?'. *European Economic Review,* 46 (9), pp. 1599-1622.

Petersen, M.A. and Rajan, R.G. (1994) 'The benefits of lending relationships: Evidence from small business data'. *Journal of Finance,* 49 (1), pp. 3-37.

Petersen, M.A. and Rajan, R.G. (1995) 'The effect of credit market competition on lending relationships'. *The Quarterly Journal of Economics,* 110 (2), pp. 407-443.

Pilloff, S. (1999) 'Does the presence of big banks influence competition in local markets?'. *Journal of Financial Services Research,* 15 (3), pp. 159-177.

Prasad, S. (2011) 'Regulators probe whether banks colluded in Libor: report'. *Reuters,* 14 April.

Rajan, R. (1994) 'Why bank credit policies fluctuate: a theory and some evidence'. *Quarterly Journal of Economics,* 109 (2), pp. 399-441.

Rajan, R.G. (2006) 'Has finance made the world riskier?'. *European Financial Management*, 12 (4), pp. 499-533.

Repullo, R. (2004) 'Capital requirements, market power, and risk-taking in banking'. *Journal of Financial Intermediation*, 13 (2), pp. 156-182.

Rochet, J.C. and Vives, X. (2004) 'Coordination failures and the lender of last resort: was Bagehot right after all?'. *Journal of the European Economic Association*, 2 (6), pp. 1116-1147.

Roodman, D. (2009) 'How to do xtabond2: An introduction to difference and system GMM in Stata'. *Stata Journal*, 9 (1), pp. 86-136.

Ross, S.A. (1977) 'The determination of financial structure: the incentive-signalling approach'. *The Bell Journal of Economics*, 8 (1), pp. 23-40.

Ross, T.W. (1992) 'Cartel stability and product differentiation'. *International Journal of Industrial Organization*, 10 (1), pp. 1-13.

Ruckes, M. (2004) 'Bank competition and credit standards'. *The Review of Financial Studies*, 17 (4), pp. 1073-1102.

Sapienza, P. (2002) 'The effects of banking mergers on loan contracts'. *Journal of Finance*, 57 (1), pp. 329-367.

Scharfstein, D.S. and Stein, J.C. (1990) 'Herd behavior and investment'. *American Economic Review*, 80 (3), pp. 465-479.

Sharpe, S.A. (1990) 'Asymmetric information, bank lending, and implicit contracts: a stylized model of customer relationships'. *Journal of Finance*, 45 (4), pp. 1069-1087.

Shleifer, A. and Vishny, R. (2010) 'Unstable banking'. *Journal of Financial Economics*, 97 (3), pp. 306-318.

Silva-Buston, C. (2019) 'Systemic risk and competition revisited'. *Journal of Banking and Finance*, 101, 188-205.

Smirlock, M. (1985) 'Evidence on the (non) relationship between concentration and profitability in banking'. *Journal of Money, Credit and Banking*, 17 (1), pp. 69-83.

Spokeviciute, L., Keasey, K. and Vallascas, F. (2019) 'Do financial crises cleanse the banking industry? Evidence from US commercial bank exits'. *Journal of Banking and Finance*, 99, pp. 222-236.

Stein, J.C. (2002) 'Information production and capital allocation: Decentralized versus hierarchical firms'. *Journal of Finance*, 57 (5), pp. 1891-1921.

Stiroh, K.J. and Rumble, A. (2006) 'The dark side of diversification: The case of US financial holding companies'. *Journal of Banking and Finance,* 30 (8), pp. 2131-2161.

Tasca, P., Mavrodiev, P. and Schweitzer, F. (2014) 'Quantifying the impact of leveraging and diversification on systemic risk'. *Journal of Financial Stability,* 15, pp. 43-52.

The Economist (2014) 'Pressures is intensifying on Russia's banking sector' 27 December.

Tran, V.T., Nguyen, H. and Lin, C.T. (2017) 'Herding behaviour in the Australian loan market and its impact on bank loan quality'. *Accounting and Finance,* 57 (4), pp. 1149-1176.

Uchida, H. and Nakagawa, R. (2007) 'Herd behavior in the Japanese loan market: evidence from bank panel data'. *Journal of Financial Intermediation,* 16 (4), pp. 555-583.

Uchida, H. and Tsutsui, Y. (2005) 'Has competition in the Japanese banking sector improved?'. *Journal of Banking and Finance,* 29 (2), pp. 419-439.

Upper, C. (2011) 'Simulation methods to assess the danger of contagion in interbank markets'. *Journal of Financial Stability,* 7 (3), pp. 111-125.

VanHoose, D. (2017) *The industrial organization of banking: Bank behavior, market structure, and regulation.* 2nd edn. Berlin, Heidelberg: Springer Berlin Heidelberg.

Veronesi, P. and Zingales, L. (2010) 'Paulson's gift'. *Journal of Financial Economics,* 97 (3), pp. 339-368.

Vietnam Investment Review (2006) 'RoK probe into bank collusion.', 12 June, pp. 23.

Vives, X. (1996) 'Social learning and rational expectations'. *European Economic Review,* 40 (3), pp. 589-601.

Wagner, W. (2010) 'Diversification at financial institutions and systemic crises'. *Journal of Financial Intermediation,* 19 (3), pp. 373-386.

Wooldridge, J.M. (2002) *Econometric analysis of cross section and panel data.* Cambridge, Massachusetts: MIT Press.

Wooldridge, J.M. (2016) *Introductory econometrics : a modern approach.* 4th edn. Boston, MA: Cengage Learning.

Windmeijer, F. (2005) 'A finite sample correction for the variance of linear efficient two-step GMM estimators'. *Journal of Econometrics,* 126 (1), pp. 25-51.

Wintoki, M.B., Linck, J.S. and Netter, J.M. (2012) 'Endogeneity and the dynamics of internal corporate governance'. *Journal of Financial Economics*, 105 (3), pp. 581-606.

Yamaguchi, K. (1994) 'The flow of information through social networks: diagonal-free measures of inefficiency and the structural determinants of inefficiency'. *Social Networks*, 16 (1), pp. 57-86.