Three Essays on Financial Economics of Banking: Bank Diversification, Asset Returns, and Earnings Management

Thesis

presented to the Faculty of Economics and Social Sciences

at the University of Fribourg (Switzerland)

by

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from Les Friques FR

in fulfilment of the requirements for the degree of

Doctor of Economics and Social Sciences

Accepted by the Faculty of Economics and Social Sciences

December 14th, 2015 at the proposal of

Prof. Martin Wallmeier (first supervisor) and

Prof. Dušan Isakov (second supervisor)

Fribourg, Switzerland, 2016

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Chapter 1

Introduction

This thesis is organised in three main papers that investigate different aspects of banking. In this introduction, we start by giving a brief overview of the banking industry with particular focus on the functions fulfilled by banks and on the evolution of this industry in the last few decades. In a second step, we discuss the three main studies that constitute this thesis and highlight our main contributions to the banking literature.

As noted by Shiller (2012) in his book *Finance and the Good Society*, banks have survived centuries of financial evolution, and thus have found an important niche in the economy. Banks are present in the daily lives (e.g. transaction services, money supply) of most individuals. While the form taken by banks has steadily evolved, their main (traditional) function, consisting in taking deposits to finance investments, has remained much the same. This function is often labelled as *intermediation function* consisting in channelling funds from individuals with no immediate use of their savings to individuals and firms with productive investment opportunities (Mishkin & Eakins, 2012).

In order to fulfil this main intermediation function and guarantee the attractiveness of their liquid, little risk-bearing deposits that pay a fixed interest rate, banks further contribute to three subordinated economic functions. First, banks achieve liquidity for their depositors by pooling the investments of many depositors. By keeping a sufficient amount of liquidity in reserve to cover the normal volume of withdrawals, they allow deposits backed up by illiquid investments to remain highly liquid.[1] Second, banks address a moral hazard problem that individuals seeking a return on their investments face if they try to invest directly. Individual investors may be robbed since some companies may not care about losses imposed to small investors. Banks, on the other hand, and even if they do make the occasional bad call, have numerous other investments in their portfolios, a strategy that generally helps them maintain their integrity and reputations. For this reason, depositors often perceive banks as safer and more appropriate. And third, banks address a selection bias problem. Most individuals have no way of evaluating the trustworthiness of potential investments. In contrast, banks deal on a personal basis with the businesses to which they lend money and they collect detailed information about these businesses (Shiller, 2012).

[1] This system usually works as intended, though it is vulnerable to sudden panic or bank runs. To prevent these situations from happening, governments have designed schemes such as deposit insurance, suspension of liquidity, and regulation asking banks to hold additional liquidity reserves.

Additionally to these functions, banks provide a payments system that allows financial and real resources to flow to their highest-return uses. Moreover, they are also involved in open market operations through interventions that alter their balance sheets and ultimately contribute to the monetary control mechanism. Finally, banks are an important source of funds for small borrowers who often have limited access to other sources of external finance (Berger, Kashyap, Scalise, Gertler, & M. Friedman, 1995).

As summarised by Barth, Lin, Ma, Seade, and Song (2013), various economic studies have shown that banks, as financial intermediaries, matter for human welfare through their impact on economic growth, property, entrepreneurship, labour market conditions, and economic opportunities. For example, King and Levine (1993) found strong links between various measures of financial development and economic indicators such as real GDP per capita growth, rate of physical capital accumulation and improvements in the efficiency with which economies employ physical capital. Similarly, Levine (2005) underlined the important role played by financial intermediaries and financial markets in promoting economic growth. For instance, better developed financial systems ease financing constraints on firms. Finally, results from the study of Demirgüç-Kunt and Levine (2009) suggest that improvements regarding the functioning of financial contracts, financial markets, and financial intermediaries expand economic opportunities available to individuals and reduce inequality.

The Great Recession of 2007-2009 has dramatically illustrated the impact that the banking system has on the real economy. This recession has massively affected most economic sectors, and this in almost all parts of the world. While the effects of this economic crisis have been widespread, the origin of the crisis was narrower. The economic crisis was triggered by the financial crisis that started in 2007 in the U.S.. Problems in the banking industry have spilled over into the real economy through the credit crunch that followed the start of the financial crisis. While particularly spectacular, the story in itself was, however, not new (Cetorelli, Mandel, & Mollineaux, 2012). As documented by Reinhart and Rogoff (2009), many severe economic crises have originated from financial crises throughout the centuries.

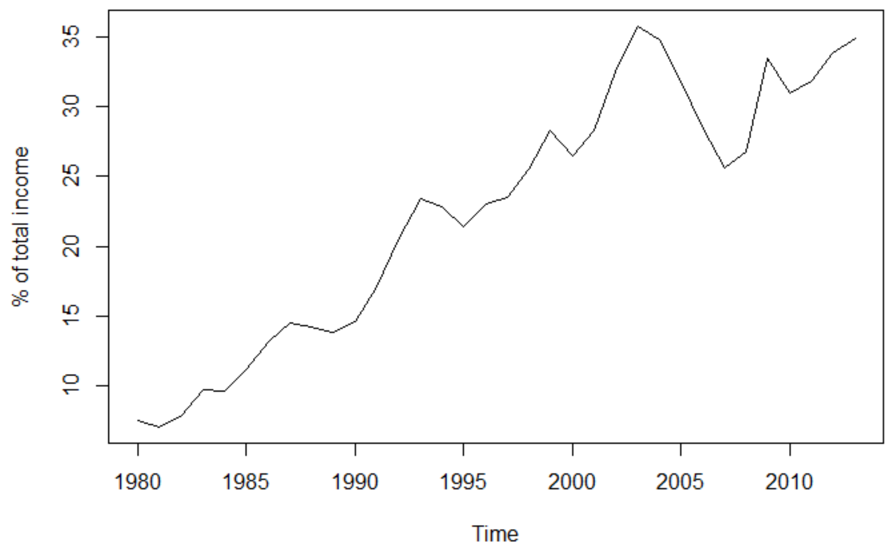
Compared to previous recessions, the economic recession that originated from the 2007-2008 financial crisis has been particularly dramatic in terms of economic output and unemployment. It reached a level of severity not seen since the Great Depression of the 1930s which was triggered by the stock market crash of 1929. Thus, the Great Depression, similar the the Great Recession, had its roots in the demise of the banking industry and in the disruption of financial intermediation.

In order to prevent a repetition of the Great Depression, governments implemented tighter banking regulations. These regulations controlled very strictly the rates at which banks could lend and borrow money, made it difficult for banks to compete with each other, and drastically restricted the scope of activities that banks could practice. These tighter regulations resulted in the banking sector being rather boring and unattractive, or at least in giving the impression that the banking industry was rather boring and unattractive (DeYoung & Rice, 2004). To illustrate this unappealing character, the banking industry was ironically labelled as following a “3-6-3 rule”. According to this “rule” that reflected the public opinion regarding the attractiveness of the banking industry during most of the period from the 1950s to the 1980s, bankers had a stable and comfortable existence. They paid a three (“3”) percent rate of interest on deposits, charged a six (“6”) percent rate of interest on loans, and then headed to the golf course at three (“3”) o’clock. While highly simplified, the 3-6-3 rule nevertheless reflects the fact that the banking industry was seen as highly noncompetitive and simplistic.

Starting in the 1980s, this rather unappealing image of the banking industry has dramatically changed. A global trend of deregulation opened up many new businesses to the banks. The most notorious example is probably the reapealing of the Glass-Steagall Act and its replacement by the Gramm-Leach-Bliley Act in 1999. The Glass-Steagall Act was enacted after the Great Depression and drastically limited the scope of commercial banks’ activities. Another example is the Second Banking Coordination Directive of 1989 in Europe (Stiroh, 2006). In addition to deregulation, technological developments like internet banking and ATMs contributed to giving a completely new visage to the banking industry (DeYoung & Rice, 2004).

Following this wave of deregulation, banks entered new businesses (e.g. investment banking, insurance, securities brokerage). These new businesses resulted in substantial amounts of noninterest income from nontraditional activities. While interest income from lending activities had long been the main source of operating income, the share of noninterest income substantially increased from the 1980s on, going in pair with the progressive deregulation that has taken place in this period (DeYoung & Rice, 2004). As illustration, we show this evolution for U.S. commercial banks on Figure 1.1.

Figure 1.1: Share of non-interest income out of total income, U.S. commercial banks 1980-2013

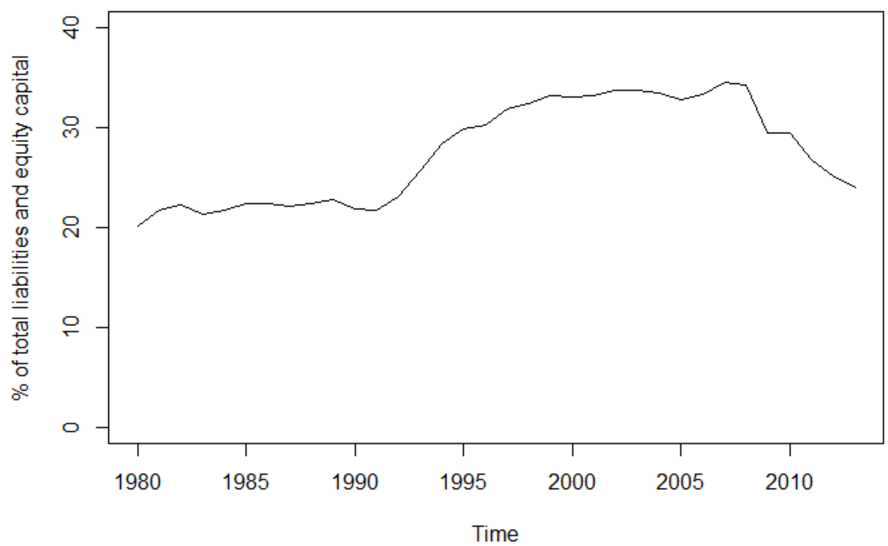


Source of the data: Federal Deposit Insurance Corporation, Historical Statistics on Banking

The fundamental changes of the last few decades have affected both the asset and the liability side of banks' balance sheets (Berger et al., 1995). Analysing fundamental changes in the U.S. banking industry between 1970 and 2003, DeYoung and Rice (2004) underlined three major developments that have decisively affected financial statements. The first major development relates to the asset side. Since the mid-1980s, the ratios of low-yielding cash balances to total assets and investments in loans to total assets have substantially declined. From 1986 to 2003, a 10 percentage point reduction in loan to total assets has been more than offset by a 12 percentage point increase in other assets such as derivatives or asset-backed securities to total assets.

The second fundamental change described by DeYoung and Rice (2004) relates to the liability side and consists in a shift from deposits funding to other funding sources. As illustration, we show this evolution for U.S. commercial banks on Figure 1.2. For the authors, these changes in the composition of banks' liabilities reflect (1) increased competition from nonbanks for household and business deposits, (2) expanded ability of large banks to raise debt in financial markets (e.g. commercial paper, subordinated debt), and (3) regulations that require banks to hold higher levels of equity.

Figure 1.2: Share of non-deposit funding out of total liabilities and equity capital, U.S. commercial banks 1980-2013



Source of the data: Federal Deposit Insurance Corporation, Historical Statistics on Banking

The third major change reported by DeYoung and Rice (2004) relates more fundamentally to the way of analysing banks. Traditionally, the focus of financial analysts has been on balance sheets. Because of the traditional intermediation function of banks, consisting in deposit-taking and loan-making, the main information regarding a bank's activity mix could be found by looking either at the asset or at the liability side of the balance sheet. Due to recent developments, DeYoung and Rice (2004) argued that the income statement has become at least as important as the balance sheet. This is especially true when it comes to assessing the respective share of commercial and investment activities.

Banks' balance sheets have become increasingly complex, opaque, and incomplete. As a result, they do not reflect all information regarding the main activities performed by banks (Bank for International Settlements, 2012; Cetorelli et al., 2012; DeYoung & Rice, 2004). An important reason is the increasing presence of off-balance-sheet (OBS) activities. Though OBS activities are not recorded on the balance sheet, they nevertheless belong to a bank's daily business and generate earnings as well as expenses. For example, Kane and Unal (1990) and Cooper, Jackson, and Patterson (2003) documented a rapid expansion in OBS activities, notably related to fee-based service activities. Similarly, Bolt and Humphrey (2010) showed that, while overall revenues of European banks increased between 1987-2006, their sources shifted from the loan-deposit rate spread to non-interest income activities. Finally, deregulation and technological changes, as well as the potential costs and benefits associated with combining bank activities of various kinds, have resulted in a wider variation of bank activities across the world.

Banks are different from firms in other industries in several ways. The biggest distinction that sets the banking sector apart from other industries is perhaps its higher degree of regulation and supervision (Mishkin & Eakins, 2012). Banking regulation affects firm-level characteristics that, in turns, affect financial ratios such as profitability, equity, or non-performing loans (Shen & Chih, 2005). Leverage is another important distinction. While high leverage is typically interpreted as financial distress in other industries, it is intrinsic in banking since the intermediation function consists in deposit-taking and results in a high level of debt (Barber & Lyon, 1997; Fama & French, 1992; Viale, Kolari, & Fraser, 2009). Financial statements in the banking industry also differ substantially from financial statements in other industries. Several positions of the balance sheet or of the income statement are proper to this industry. First, most positions on the asset and liability side are financial assets. Second, banks are characterised by specific positions such as provisions for loan losses or realisation of gains or losses on securities that do not prevail in other industries (Cohen, Cornett, Marcus, & Tehranian, 2014). Furthermore, compared to other industries, the estimation of discretionary accruals can be problematic in the banking industry (DeFond & Subramanyam, 1998). Finally, banks are highly sensitive to overall financial risk in the economy (Gandhi & Lustig, 2013).

All these differences are likely to be reflected through fundamental differences in accounting variables that reduce the comparability between banks and firms in other industries and often result in the exclusion of banks from a vast area of empirical studies in accounting and finance. Yet, these special characteristics do not make banks less worthy of rigorous empirical analyses. This situation has fostered the development of a banking-specific literature.

This thesis is organised in three main papers that relate more or less closely to several aspects of banking briefly discussed in this introduction. These papers form a unit in that they relate to topics of importance for the banking industry. The overall methodology used throughout the thesis is largely based on empirical methods. Paper 1 (corresponding to Chapter 2) investigates whether changes regarding banks' activity mix affects market valuation, therefore exploring a topic specific to the banking industry. The two remaining papers focus on research topics for which banks are typically excluded from empirical studies. Similar to Paper 1, Paper 2 (Chapter 3), also takes a market perspective and investigates whether bank stock returns can be predicted by banking industry-specific accounting ratios, profitability measures, and market anomalies that prevail in the nonfinancial industry. Paper 3 (Chapter 4) investigates earnings management, a practice that compromises the faithful representation of underlying economic conditions and riskiness. The three chapters are organised in such a way that they can be read independently. In the following, we discuss in more detail each of these three papers.

In Paper 1, we investigate the impact of bank diversification on market valuation.[2] As underlined earlier, the Glass-Steagall Act of 1933 strictly limited activity diversification in banking. However, a wave of worldwide deregulation starting in the 1980s has resulted in a progressive shift from commercial activities towards investment activities. Three studies in the recent literature have investigated valuation effects of bank diversification and reported strongly different results. Laeven and Levine (2007) found a significant diversification *discount* for a sample of international banks between 1998-2002. Baele, De Jonghe, and Vander Vennet (2007) reported a significant diversification *premium* among European banks between 1989-2004. Elsas, Hackethal, and Holzhäuser (2010) found *no direct effect* of diversification for a sample of banks in nine industrialised countries between 1996-2008, but an *indirect effect* from a positive association of diversification with

[2]The first study is a joint work with Prof. Dr. Martin Wallmeier while the second and third studies are solely my work.

profitability.

Of course, the difference in results between these studies could be explained by the geographical composition of the samples or by the different time periods analysed. For instance, Baele et al. (2007) advanced that institutional and regulatory differences between Europe and the U.S. were responsible for the different results found in their study compared to the study of Laeven and Levine (2007). However, a more careful analysis of the three studies reveals fundamental methodological differences. First, bank diversification is intimately related to another structural characteristic, which is bank type and is also typically proxied by interest-income share. As both "type" and "diversification" are measured on the basis of the share of interest income, they are closely related and have to be considered jointly (see Laeven and Levine (2007), p. 337). Yet, only Laeven and Levine (2007) correctly included these two variables in regression. Second, Elsas et al. (2010) used an estimation approach with bank fixed effect, thus focusing on the variation of individual bank value over time, while Laeven and Levine (2007) and Baele et al. (2007) used country fixed effects and were primarily interested in cross-sectional valuation differences. And third, the control variables used are not identical. For instance, Elsas et al. (2010) argued that including a profitability proxy resulted in the non-significance of diversification in their study. These fundamental methodological discrepancies substantially reduce the comparability of the results, and it is therefore difficult to assess whether the different results come from the composition of the samples analysed or from these methodological differences.

Motivated by these strongly different results, we revisit the relationship between market valuation and diversification for a sample of international banks between 1998 and 2013 that includes 19,677 bank-year observations. In order to clearly identify which factors are responsible for the different results (e.g. time period, sample composition, fundamental differences in the regression framework), we form three samples similar to those investigated in the three relevant studies and use a unified framework. Our first intended contribution is therefore to highlight the importance of using a similar methodology to guarantee a direct comparability of the results between studies looking at the same topic. Second, we aim to contribute to the discussion about institutional and geographical determinants of diversification effects by analysing the results for samples covering different geographical areas. As a third contribution, we extend the analysis of prior studies to the recent financial crisis and the following years until 2013.

Our main findings are as follows. We show that using a unified framework for the same time period leads to very similar results in the various samples investigated. Therefore, different regulatory and institutional frameworks do not appear to be responsible for differences in diversification effects. This finding underlines the importance of using an adequate regression framework in order to compare the valuation effect of diversification across geographical areas. Our results show that the differences reported in past studies are likely to reflect methodological differences. Similar to Laeven and Levine (2007), we report a diversification discount for the period 1998-2002 that is robust to the inclusion of profitability. However, this discount substantially declines over time and practically vanishes in the last period considered (2010-2013). We also report a significant premium for investment banks. Similarly to diversification, this effect diminishes over time. In addition, we show that the diversification discount is partly caused by a small number of highly valued investment banks, and therefore do not prevail uniformly in the whole sample.

In Paper 2, we investigate the predicting power of profitability, industry-specific variables, and traditional market anomalies on the cross-section of bank stock returns. We analyse 190,592 monthly returns for U.S. banks between 1980-2014. The financial literature has reported the existence of patterns predicting stock market returns (e.g. market-to-book, size or momentum) labelled as stock market anomalies because they are not explained by the CAPM. Since most asset pricing studies exclude financial institutions, and since only few industry-specific studies exist (e.g. Barber and Lyon (1997)), little is known about patterns affecting banks' cross-sectional returns. In particular, the profitability premium, which has attracted particular attention in recent years (e.g. Fama and French (2006), Fama and French (2008), Novy-Marx (2013)), remains unexplored within the banking industry.

Our first intended contribution is to explore the existence of a profitability premium within this industry. As a second contribution, we look at the predicting power of several industry-specific variables. Because of the different nature of banks compared to firms in other industries, there may exist important links between industry-specific variables and the cross-section of stock returns

(Cooper et al., 2003). As our last contribution, we investigate the predicting power of several well-known market anomalies such as size, market-to-book, and past performance at different horizons. To our knowledge, the momentum anomaly has never been explored within the banking industry.

Our main findings are as follows. Contrasting with clear-cut evidence presented by Novy-Marx (2013) for the nonfinancial industry, we find only limited evidence regarding the predicting power of profitability in banking. While we find convincing evidence suggesting a positive relationship between profitability and expected returns in Fama and MacBeth (1973) cross-sectional regression, further investigation shows that this result is largely driven by characteristics of small market capitalisations. Among traditional market anomalies, we find strong evidence suggesting that book-to-market and past performance at a horizon of one month (short-term return reversal) can predict the cross-section of expected returns. Among industry-specific variables, our results show that loan loss provisions, loan share, and activity diversification can also predict the cross-section of stock market returns. Therefore, we argue that these variables can be considered as serious candidates for the development of a banking industry-specific asset pricing model. The predicting power of past performance at a horizon of one month stands out from the other variables considered both in terms of statistical and economic significance.

Paper 3 deals with earnings management in banking. We adopt a distributional approach and investigate 27,585 bank-year observations for a sample of international banks between 1999 and 2013. Similar to asset pricing studies, banks are often excluded from earnings management studies. For the banking industry, only Shen and Chih (2005) explore earnings management using a distributional approach. They found evidence of a kink around zero earnings in the distribution of reported earnings. Similar to others (e.g. Burgstahler and Dichev (1997), Degeorge, Patel, and Zeckhauser (1999)), they interpreted this kink as evidence of earnings management without further investigation. Our study goes one step further in the sense that it does not only explore the existence of a kink, but also investigates what earnings streams are responsible for the formation of the king, and whether earnings management is behind the kink.

Our approach to answer these questions is inspired by the study conducted by Dechow et al. (2003) for nonfinancial firms. First, we investigate the presence of a smooth pre-managed earnings distribution similar to the one reported by Dechow et al. (2003). We further analyse the presence of a kink around zero earnings in the distribution of reported earnings. Finally, we investigate earnings streams that occur between pre-managed earnings and reported earnings in order to investigate which specific earnings streams are responsible for the formation of the kink. While most empirical studies attribute the presence of a kink to earnings management without further analysis, our approach allows us to assess whether this kink can actually be attributed to earnings management.

The main results of this study are as follows. We show the existence of a smooth pre-managed earnings distribution (Pre-impairment operating profit). We further document the progressive formation of a kink around zero earnings taking place in the distribution of earnings measures further down the income statement and culminating in the distribution of Net income. The analysis of earnings streams occurring in-between shows that banks with relatively high pre-managed earnings are decisively shifted to the left while banks with small positive earnings are only moderately shifted, thus causing the kink. This partial shift reflects higher earnings streams among banks with high pre-managed earnings relative to banks with small pre-managed earnings. The decomposition of total earnings stream shows that banks with higher pre-managed earnings have higher impairment charges on loans, securities, and other credits as well as higher tax expenses. While the difference regarding impairment charges is likely to reflect at least some degree of earnings management, the kinking effect of taxation is more difficult to reconcile with an earnings management explanation since banks with higher earnings can rationally be expected to have larger tax expenses. Thus, we conclude that earnings management is only a partial explanation for the kink, and that the magnitude of the kink can only be partially attributed to earnings management.

Chapter 2

The Valuation of Diversified Banks: New Evidence

The Valuation of Diversified Banks: New Evidence

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January 25, 2016

Abstract

We reconsider the effect of diversification on bank valuation. Prior studies in the recent literature have come to strongly different results, including a significant diversification discount, a significant diversification premium, and no direct effect at all. The differences are in part attributed to specifics of the legal and regulatory environment in Europe and the U.S.. In contrast, we argue that the differences arise from confounding the effects of diversification (specialised banks vs. diversified banks) and bank type (investment banks vs. commercial banks) in some of the studies. In a unified framework in which the effects of diversification and bank type can clearly be identified, results are similar for U.S. and European banks and across regulatory regimes. At the beginning of our sample period from 1998 to 2013, we find a significant diversification discount, which declines during the years before the financial crisis and practically vanishes afterwards.

Keywords: Banking, Firm valuation, Diversification, Conglomerate discount, Universal banking, Economies of scope, Agency costs.

JEL Classification Numbers: G21, G24, G28, G34, L22, L25.

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2.1. Introduction

The association between the diversification of a bank and its valuation is of great interest for the governance of banks and for bank regulation. As discussed by Laeven and Levine (2007) and Elsas et al. (2010), different theoretical hypotheses on the impact of diversification on valuation exist. On the one hand, diversification may allow economies of scope and synergies between the different business units, for example by providing financial consulting services to firms that are also loan clients. On the other hand, diversification can give rise to conflicts of interest and agency costs, and it may result in a more complex organisational structure and a less focused customer orientation. It is not clear from theory which of these factors prevail, so that empirical studies are important to estimate the net effect of diversification.

Bank diversification measures are often based on the share of interest income in total operating income. A bank is considered as fully specialised if the interest-income share is zero or one. In contrast, a bank is more or less diversified if it earns interest income from lending as well as non-interest income from commissions or trading. We may consider a bank with equal weights of interest income and non-interest income as fully diversified, so that the highest degree of diversification is reached when the interest-income share is 50%.

Bank diversification is intimately related to another structural characteristic, which is bank type. The "type" characteristic is also typically proxied by interest-income share. A fully specialised investment bank will be assigned a value of zero because it does not operate in interest-earning business, while a fully specialised commercial bank only earns interest income and thus obtains a value of one. Banks combining investment business and commercial banking are assigned a value in-between. As both "type" and "diversification" are measured on the basis of the share of interest income, they are closely related and have to be considered jointly (see Laeven and Levine (2007, p. 337)). The estimation of the diversification effect will likely be distorted if the type effect is not simultaneously taken into account, and vice versa.

The same conclusion holds if interest-income share is replaced by the share of loan assets in total assets, which is an alternative proxy proposed in the literature (Laeven & Levine, 2007).

Again, the type scale goes from zero for pure investment banks to one for pure commercial banks, and the diversification scale goes from zero for both pure investment banks and pure commercial banks to one for banks with equal weights of the two businesses (loan share of 50%). As before, the diversification effect cannot be isolated from the type effect if only one of the variables is included as an explanatory variable.

In the recent literature, three studies have investigated valuation effects of bank diversification (Laeven and Levine (2007); Baele et al. (2007); Elsas et al. (2010)). They come to strongly different results: Laeven and Levine (2007) find a significant diversification discount; Baele et al. (2007) report a significant diversification premium; and Elsas et al. (2010) find no direct effect of diversification, but an indirect effect from a positive association of diversification with profitability. There are several differences between the studies which could explain these results, e.g. the sample composition and the sample period. However, a more fundamental difference is that only Laeven and Levine (2007) consider bank type and diversification jointly, while the other studies do not take the close relation of these variables into account. We show that this problem can explain the different results. Therefore, our first and main intended contribution is to highlight the importance of this methodological issue and to reconcile the different results from previous literature by using a comprehensive framework including type and diversification.

Controlling for bank type also allows us to shed new light on institutional and geographical determinants of diversification effects, which is the second contribution of this paper. Baele et al. (2007) argue that the relation between diversification and bank value is different in Europe relative to the U.S., because the European banking sector had been deregulated by the Second Banking Coordination Directive already in 1989, when in the US, the Glass-Steagall Act was still in force. Thus, European banks were allowed to diversify earlier and more broadly. As a consequence, potential advantages of diversification might have been exploited more thoroughly in Europe relative to the U.S.. Consistent with this hypothesis, Baele et al. (2007) find evidence of an income-based diversification premium, contrary to the results of Laeven and Levine (2007) for a broad international sample. However, as argued above, it is not clear which factors are responsible for the different results. Similar arguments apply to the study of Elsas et al. (2010) which is based on a sample of nine developed countries including European countries and the U.S.. In this study, we provide comparable results for the samples of these three previous papers by unifying the time periods, the estimation approach, the type and diversification proxies and the control variables. Our hypothesis is that previous results might be driven by differences in the estimation method rather than geographical or regulatory factors. After all, at the end of the 1990s, the Glass-Steagall Act had already been substantially weakened, and internationally operating banks had become quite similar.

Our third contribution is to extend the analysis to the recent financial crisis and the following years until 2013. For prior periods, there is strong evidence of a valuation premium for banks relying predominantly on investment activities (Baele et al., 2007; Laeven & Levine, 2007). However, during times of financial distress, commercial activities have been shown to be more stable and recession-proof than investment activities (DeYoung & Roland, 2001), which suggests that the premium associated with investment banking may have diminished or even reversed in the aftermath of the global financial crisis. As highlighted by Elsas et al. (2010), it is also plausible to assume that the crisis has led to a re-evaluation of the costs and benefits of diversification: on the one hand, diversified banks could be better able to absorb shocks, on the other hand, they might suffer disproportionately from a negative outlook on the investment banking branch. Moreover, the financial crisis revealed weaknesses of individual banks (e.g. Lehman Brothers, Freddie Mac) going beyond their classification as commercial or investment banks. Thus, it is possible that a shift in valuation from activity-related criteria towards more individual criteria has taken place. Among the three main studies cited above, only Elsas et al. (2010) study the sub-prime crisis. While the main part of their study investigates the period from 1996 to 2006, an additional analysis extends to the years from 2006 to 2008. However, the authors focus on the variation of individual bank value over time, whereas our study − in line with Laeven and Levine (2007) and Baele et al. (2007) − is primarily interested in cross-sectional valuation differences. This difference is reflected in an estimation approach with bank fixed effects in Elsas et al. (2010) and country fixed effects in Laeven and Levine (2007), Baele et al. (2007) and this study.

Finally, we propose a robustness check based on robust regressions which is motivated by the fact that the number of investment banks is small compared to the number of commercial banks, and there is concern that extreme observations for some investment banks might strongly affect the estimation results.

Our main results can be summarised as follows. When controlling for bank type, the diversification effect does not seem to be influenced by geographical or regulatory factors. In each subperiod and both for income- and asset-based measures, the effects of bank type and diversification are similar for the three subsamples of the main prior studies. In particular, we do not confirm that European banks tend to achieve diversification benefits. In the first subperiod (1998-2002), we find a significant premium for investment banks and a significant diversification discount. However, this result is partly driven by a small number of rather extreme observations for investment banks, so that the effects are considerably smaller in a robust regression. The diversification discount declines during the years before the financial crisis and practically vanishes in the last subperiod (2010-2013).

The remainder of the paper is structured as follows. The next section presents the definitions of bank type and diversification and discusses how the corresponding effects were estimated in prior studies. In Section 2.3, we describe the data and the variables used in the empirical analysis. In Section 2.4, we present the main results, followed by robustness tests in Section 2.5. Section 2.6 concludes.

2.2. Bank type and diversification in prior literature

The three most relevant prior studies on the association of bank valuation and bank diversification (Laeven and Levine (2007); Elsas et al. (2010); Baele et al. (2007)) are based on data for listed banks from the Bankscope database of Bureau van Dijk. Laeven and Levine (2007) use data from 43 countries for the period 1998-2002. After excluding small banks with less than US$100 million in total assets, their final dataset includes 3415 bank-year observations. Baele et al. (2007) use data from 17 European countries (EU15, Norway and Switzerland) over the period 1989-2004. Their selection rules result in a final dataset of 143 banks and 1200 bank-year observations. Elsas et al. (2010) include large banks from nine developed countries (Australia, Canada, France, Germany, Italy, UK, USA, Spain and Switzerland) from 1996 to 2008. Only banks with total assets exceeding US$1 billion in at least one year of the sample period are included. The final sample contains 380 banks covering 3348 bank-year observations.

The three studies use the following "type" and "diversification" measures, with x defined as the ratio of net interest income to total operating income (interest-income share):

$$Type_1 = x \tag{2.1}$$

$$Type_2 = x/(1-x) \tag{2.2}$$

$$Diversification_1 = 1 - |2x - 1| \tag{2.3}$$

$$Diversification_2 = 1 - \left(x^2 + (1-x)^2\right), \tag{2.4}$$

Figure 2.1 shows $Type_1$ and $Type_2$ in the left panel and $Diversification_1$ and $Diversification_2$ in the right panel. While the type proxies increase monotonically with interest-income share, the diversification proxies reach a maximum at an interest-income share of 50%. The two diversification measures are similar to each other, while the type measures are clearly different. $Type_2$ has a peculiar form going to infinity when interest-income share approaches one, which implies that tiny changes of interest-income share yield large changes in $Type_2$. For instance, the $Type_2$-impact of a change in interest-income share from 0% to 50% is the same as the impact of a change from 90% to 91%. This pattern does not capture the common understanding of bank type so that we do not regard $Type_2$ as a meaningful alternative to the type proxy $Type_1$.

[**Figure 2.1 about here**]

The main estimated regression equation of Laeven and Levine (2007, p. 347, Table 4, Col. 5) is:[1]

$$Q(LL) = Constant - 0.220 \cdot Type_1 - 0.080 \cdot Diversification_1 + Controls \tag{2.5}$$

where $Q(LL)$ is Tobin's Q measure. The incremental effect of type and diversification on Tobin's Q is illustrated in the left panel of Figure 2.2. The effect of type can be seen from the negative overall slope implying a higher value $Q(LL)$ of pure investment banks (interest-income share of 0) relative to pure commercial banks (interest-income share of 1). The diversification discount reported by Laeven and Levine (2007) is apparent from the kink in the profile at level 0.5 indicating that diversified banks are valued below a linear combination of pure commercial banks and pure investment banks.

[**Figure 2.2 about here**]

The relevant regressions of Baele et al. (2007, p. 2012, Table 3, Cols. 1, 2, 5) are:[2]

$$Q(BJV) = Constant + 0.0949 \cdot (1 - Type_1) + Controls \tag{2.6}$$

$$Q(BJV) = Constant + 0.0593 \cdot (1 - Type_1) + 0.0645 \cdot (1 - Type_1)^2 + Controls \tag{2.7}$$

$$Q(BJV) = Constant + 0.0449 \cdot Diversification_1 + Controls \tag{2.8}$$

[1] We refer to Col. 5 as the main regression for the following reasons: Cols. 1-4 use another dependent variable ("Excess value" instead of Tobin's Q) which reduces the comparability of results with the other studies. In Cols. 6-8, the set of control variables is slightly different, but with minimal impact on the relevant coefficients.

[2] We refer to Cols. 1, 2, 5 as the relevant regressions because they are based on income-based measures, while Cols. 3, 4, 6 of the same table use assets-based measures of Type and Diversification.

where $Q(BJV)$ is a modified version of Tobin's Q.[3] The estimated linear regression (2.6), which is illustrated as a solid straight line in the middle panel of Figure 2.2, shows a significantly higher valuation of investment banks compared to commercial banks, which is in line with the finding of Laeven and Levine (2007). In addition, the estimated quadratic regression (2.7) is convex, which is consistent with a diversification discount, again in line with Laeven and Levine (2007) (dotted line, middle panel of Figure 2.2). It is not clear, however, if the discount is significant.[4] The third regression (2.8) shows a significantly *positive* coefficient for $Diversification_1$. This is regarded as evidence of a diversification *benefit*: "The result is [..] in contrast to the conclusion of Laeven and Levine [..] who obtain a diversification discount in financial conglomerates (for a worldwide sample). Since we use a similar measure of revenue diversification, the most probable explanation for the difference is the scope of the sample. The fact that diversified European banks have a longer track record and have committed sufficient operating and managerial resources to all these activities may explain the conviction that they will generate adequate profits" Baele et al. (2007, p. 2013).

However, the illustration of the third regression in the middle panel of Figure 2.2 (dashed triangular line) suggests a different interpretation. Because the type variable is not included in regression (2.8), the triangular structure (V-shape or inverted V-shape) of the diversification variable is imposed on the data. This is in conflict with the fact that investment banks are more highly valued than commercial banks, as is apparent from regressions (2.6) and (2.7). In this situation, regression (2.8) can match the observations either for investment banks (low interest-income share) or commercial banks (high interest-income share), but not both. Since the number of banks with a pronounced commercial banking profile is by far larger than the number of investment banks, commercial banks are more important for the estimation. As a result, the estimated regression function fits these observations (with high interest-income share) well, while the higher valuation of investment banks (with low interest-income share) must be ignored. To avoid this misspecification, $Type_1$ needs to be added to regression (2.8) (see also Laeven and Levine (2007,

[3] The authors mention that results based on the traditional Tobin's Q measure are similar (Baele et al. (2007), p. 2020).

[4] The linear and quadratic term are individually insignificant due to multicollinearity, but jointly significant (Baele et al. (2007), p. 2012). The likelihood ratio test for the fit of the quadratic model compared to the linear model is not reported.

p. 337)). In this case, we would expect to obtain a negative sign of the diversification variable and an inverted L-shape for the combined effect, in line with the convex regression function (2.7). We conclude that the diversification benefit reported in Baele et al. (2007) most probably comes from not jointly considering type and diversification. The data are more in line with a diversification discount.

The relevant regression in Elsas et al. (2010, p. 1279, Table 3, Col. 3) is:[5]

$$MTB = 1.38 \cdot Diversification_2 - 0.50 \cdot (Diversification_2)^2 - 0.01 \cdot Type_2 + Controls, \quad (2.9)$$

where MTB is the ratio of the market value of equity to the book value of equity. The incremental effect of interest-income share on MTB is shown in the right panel of Figure 2.2. The graph indicates a considerable diversification premium. Individually, the regression coefficients of $Diversification_2$ and $Diversification_2^2$ are not significant, but this might well be due to the almost perfect collinearity of the two variables.[6] However, regression (2.9) suffers from the same problem as regression (2.8) of Baele et al. (2007) because bank type is not adequately controlled for. As mentioned earlier, the nonlinear $Type_2$ variable cannot account for the valuation difference between investment banks and commercial banks. Thus, the structure of the diversification variable with a minimum or maximum at 50% interest-income share is again imposed on the data, which means that the regression is misspecified. This methodological problem is important enough to explain the conflicting results of the three studies. The following empirical study aims to examine diversification effects while controlling for bank type.

[5] This regression is relevant for our comparison, because the diversification proxy is only based on interest-income share. In other specifications, a further decomposition of non-interest income into fee-based, trading, and commission income is used.

[6] The joint significance of both terms is not reported.

2.3. Data and variables

2.3.1. Sample of banks

We obtain bank-level data for listed banks from Bankscope of Bureau van Dijk. Data on market capitalisation come from Thomson Reuters Datastream. We use macroeconomic control variables from the World Bank, regulatory data from Barth, Caprio, and Levine (2013), and a financial freedom index from the Heritage Foundation. Our sample covers the 16-year period from 1998 to 2013. This period includes different business cycles and stock market conditions (e.g. Dot-com bubble, economic expansion of the early 2000s, sub-prime crisis, sovereign debt crisis). Our sample is free from survivorship bias since we also consider banks that have been delisted during the sample period. Following Laeven and Levine (2007), we exclude small banks with less than US$ 100 million in total assets to enhance comparability across countries. We exclude banks that are engaged in neither investment banking nor deposit-taking and loan-making. We also eliminate banks classified as Islamic banks because their accounting information does not match with the rest of the sample. Finally, we exclude banks with missing data on accounting variables.

We build three subsets of banks corresponding to the samples used in the three prior studies of interest. The first sample, following Laeven and Levine (2007), includes banks from all countries worldwide ("Whole sample"). The second subset, following Baele et al. (2007), includes banks from 17 European countries ("European sample"; EU 15 + Norway and Switzerland). Finally, the third subset, following Elsas et al. (2010), consists of banks from nine industrialised countries ("Industrialised countries sample"; Australia, Canada, France, Germany, Italy, UK, USA, Spain, and Switzerland).

We divide the total period into four subperiods to detect a possible evolution over time and to allow comparison with existing studies. The first subperiod (1998-2002) corresponds roughly to the Dot-com bubble and matches the period considered by Laeven and Levine (2007). The second subperiod (2003-2006) corresponds to the economic expansion of the early 2000s, the third subperiod (2007-2009) to the financial crisis, and the fourth subperiod (2010-2013) to the post-financial crisis period.

2.3.2. Baseline specification

In order to examine how diversification affects bank valuation while controlling for other potential determinants, we estimate the following panel regression as our baseline empirical specification:

$$\begin{aligned} Q_{i,t} = \alpha_0 + \alpha_1 Type_{i,t} + \alpha_2 Diversification_{i,t} + \boldsymbol{\alpha_3} \boldsymbol{X}_{i,t}^{Bank} + \boldsymbol{\alpha_4} \boldsymbol{X}_{i,t}^{Macro} + \boldsymbol{\alpha_5} \boldsymbol{X}_{i,t}^{Reg} \\ + \theta_{j(i)} + \gamma_t + \epsilon_{i,t}, \end{aligned} \tag{2.10}$$

where $Q_{i,t}$ is Tobin's Q of bank i at time t, $Type$ and $Diversification$ are the main variables of interest as explained above, and $\boldsymbol{X}^{Bank}$, $\boldsymbol{X}^{Macro}$, $\boldsymbol{X}^{Reg}$ are vectors of bank-level, macroeconomic and regulatory control variables. We denote by $j(i)$ the country of origin of bank i. The regressions include country (θ) and year (γ) fixed effects.

2.3.3. Variables

In the following, we describe the included variables in more detail. Table 2.1 gives an overview and specifies the data sources. Summary statistics are shown in Table 2.2 and country-specific summary statistics in Table 2.3.

[Table 2.1 about here]

[Table 2.2 about here]

Tobin's Q

We define Tobin's Q as

$$Q = \frac{Market\ value\ of\ equity + Book\ value\ of\ debt}{Book\ value\ of\ equity + Book\ value\ of\ debt} \tag{2.11}$$

We use the market value of equity three months after the fiscal year end to account for the typical delay in the release of accounting information. Following Bolt, de Haan, Hoeberichts, van Oordt, and Swank (2012), we winsorise Tobin's Q at 1% and 99% to mitigate the impact of outliers on regression estimates.

Bank type and diversification

We use the same income-based and asset-based measures of bank type and diversification as Laeven and Levine (2007). The income-based measures are identical to $Type_1$ and $Diversification_1$ as defined in Eq. (2.1) and (2.3). The asset-based bank type measure equals loans to total earning assets, where total earning assets include loans, securities, and investments. Large values mean that banks specialise in commercial activities, lower values indicate a higher degree of investment activities. The asset-based diversification measure is defined in a similar way as $Diversification_1$:

$$Asset\text{-}based\ Diversification = 1 - \left| \frac{Net\ Loans - Other\ Earning\ Assets}{Total\ Earning\ Assets} \right|. \tag{2.12}$$

It is an open question whether the income-based measures or the asset-based measures are more appropriate. Laeven and Levine (2007) favour the asset-based definition due to potential measurement problems faced by income-based measures. A particular concern is that loans granted by commercial banks can yield fee income which is attributed to investment activities. However, the asset-based measure may also be problematic because of the increased presence of off-balance sheet activities in past decades (Cooper et al., 2003; Kane & Unal, 1990). Since these items are not formally booked, an asset-based measure may underestimate diversification. As there is no clear preference, we show all results for asset-based as well as income-based measures of bank type and diversification.

Table 2.4 shows the correlations between bank type and diversification for the whole sample. Asset-based measures and income-based measures are significantly but not strongly correlated (0.39 for bank type, 0.14 for diversification), suggesting that they measure different aspects of bank activities.

[Table 2.4 about here]

Figure 2.3 shows boxplots per year to illustrate the evolution of the type and diversification measures over time (upper graphs: type; lower graphs: diversification). The median of type is mostly near 0.75, and the 25%-quantile is still clearly above 0.5. This indicates that the vast majority of banks is more oriented towards commercial banking than investment banking. Banks with an interest-income share or net loans share below 0.25 are rare and typically identified as outliers in the boxplot diagrams. The upper graphs show a noticeable spike in the share of interest income in the crisis year of 2008. This echoes findings from DeYoung and Roland (2001) for prior episodes of financial distress and confirms that commercial activities seem more stable and recession-proof than investment activities. Further evidence is found in the lower graphs of Figure 2.3 which show a decrease of the overall level of diversification in 2008. The median of net loans share tends to increase in the five years before the financial crisis and to slightly decrease again since 2009. However, the distribution of the type and diversification measures does not seem to be strongly or systematically different in the years before and after 2008.

[**Figure 2.3 about here**]

Bank-level control variables

We investigate more closely whether different funding structures have an impact on bank valuation. The International Monetary Fund (2013) documents an increase in the share of wholesale funding and a simultaneous decrease in the share of customer deposits in the years leading to the financial crisis. A higher share of wholesale funding is associated with a higher level of bank distress. In fact, one of the triggers of this crisis is seen in the incapacity of US and European banks that heavily relied on short-term wholesale funding to renew their expiring funding sources (Claessens et al., 2012; International Monetary Fund, 2013; Laeven, 2011). These results underline the stable character of deposit funding compared to market funding, presumably because deposits are usually covered by government guarantees (see, e.g., Ivashina and Scharfstein (2010) or Beltratti and Stulz (2012)). However, a higher share of wholesale funding may also indicate higher creditworthiness through the ability to raise funds in wholesale capital markets (Demirgüç-Kunt & Huizinga, 2010).

For the empirical analysis, we construct two measures of banks' funding structures. The first, deposit share, is defined as the share of customer deposits in total liabilities. The second variable, wholesale share, is defined as the share of wholesale funding (total short-term funding minus customer deposits) in total liabilities.

An important theoretical determinant of Tobin's Q is a bank's earnings potential because the market value of equity includes expected earnings that are not yet realised and therefore not captured in the book value of assets. In robustness checks, Elsas et al. (2010, Table 7, p. 1283) find that controlling for profitability is crucial because the significant effect of diversification disappears when a profitability measure is included. The following five control variables are included as proxies for different aspects of the earnings potential:

(1) The ratio of operating profit to total assets.[7] (2) The cost-to-income ratio as a standard bank-efficiency measure (Elsas et al., 2010). (3) The ratio of loan loss provisions to net loans. Under fair value accounting, loan loss provisions negatively affect earnings and capital. Thus, a high ratio indicates a poor quality of the loan portfolio. However, loan loss provisions are commonly used for income smoothing purposes (Ahmed, Takeda, & Thomas, 1999; Beatty, Ke, & Petroni, 2002; Fonseca & Gonzalez, 2008) and could therefore be a weak signal of asset quality. (4) The Z-score as a measure of bank-level risk and the distance to default.[8] (5) Finally, we include the change in total assets as a proxy for growth opportunities (Laeven & Levine, 2007).

We further include the natural log of total assets as a measure of bank size. While bigger banks may benefit from economies of scale or from their too-big-to-fail status, they may also grow beyond their optimal size and suffer from diseconomies of scale or exacerbated agency costs (Demirgüç-Kunt & Huizinga, 2013). Our last bank-level control variable is the ratio of common equity to total assets. Because equity represents a buffer against losses but is commonly regarded as expensive, a higher equity ratio is expected to be associated with higher valuation in times of financial distress, but with lower valuation during good times.

[7] We use operating profit rather than net income because it is commonly argued that gross or operating profit, reflecting a firm's core activity, is a better proxy for profitability (see Novy-Marx (2013); Yao and Liang (2005); and Trueman, Wong, and Zhang (2000)).

[8] We update the Z-score following the recommendation of Lepetit and Strobel (2013).

Macroeconomic and regulatory control variables

Our macroeconomic control variables are inflation, the GDP growth rate and GDP per capita. To capture the regulatory environment in different countries, we include indexes provided by Barth, Caprio, and Levine (2013). These indexes reflect country-specific capital stringency, diversification guidelines, restrictions on bank activities, restrictiveness with respect to financial conglomerates, financial statement transparency, deposit insurance scheme, and supervisory power. Finally, we use the financial freedom index of the Heritage Foundation, which is a measure of banking independence from government control.

2.4. Empirical Results

Our analysis consists of 24 regressions, corresponding to all combinations of three subsets (Whole, Europe, Industrialised), four subperiods (1998-2002, 2003-2006, 2007-2009, 2010-2013), and two definitions of type and diversification (asset-based, income-based). We summarise the estimation results in tabular and graphical form. Tables 2.5 to 2.7 show results for the three subsets, in columns 1-4 for asset-based measures of type and diversification, and in columns 5-8 for income-based measures. The p-values are based on standard errors adjusted for clustering at the bank level (Laeven & Levine, 2007). The macroeconomic and regulatory control variables are included in the estimations, but for the sake of brevity, the coefficients are not displayed. Figures 2.4 and 2.5 illustrate the combined effect of type and diversification for the income-based and asset-based definitions. As emphasised earlier, type and diversification are strongly related because they are both defined as a function of the same base variable (interest-income share or net loans share). To capture the combined effect, we plot the predicted partial response of Tobin's Q to type and diversification in a graph with interest-income share or net loans share on the horizontal axis.[9] An effect of type can be seen from the difference of Tobin's Q at the left and right edges, and an effect of diversification is reflected in a kink of the profile in the middle. Figure 2.4 illustrates the results for the income-based measures, Figure 2.5 for the asset-based measures. Each figure contains 12 graphs, for combinations of three subsets (rows) and four subperiods (columns).

[Table 2.5 about here]

[Table 2.6 about here]

[9] All other explanatory variables are fixed on their mean level. One possible issue with the line of best fit to model a partial relationship is the presence of high correlations with other independent variables. We check for the presence of high correlations between the variables of interest (type and diversification) and the other independent variables using a correlation matrix, but found no pairwise correlations above 0.4. Thus, high correlations should not be an issue.

[Table 2.7 about here]

[Figure 2.4 about here]

[Figure 2.5 about here]

The two figures allow a quick overview across samples by comparing the vertically aligned graphs. It turns out that these are always very similar, which indicates that the valuation impact of type and diversification is not different in Europe compared to the U.S. or other industrialised countries. Therefore, our evidence does not support the hypothesis of Baele et al. (2007) that the particular historical and regulatory conditions of diversification in Europe are reflected in a valuation premium of diversified banks. The evidence also contradicts the hypothesis of Elsas et al. (2010) that no direct effect of diversification exists when profitability is controlled for. Therefore, our empirical results are consistent with our critical remarks on Baele et al. (2007) and Elsas et al. (2010) in Section 2.2.

In the first period (1998-2002), we find a significant diversification discount and thus confirm the finding of Laeven and Levine (2007) for the same period. We report highly significant coefficient estimates of respectively -0.071 (asset-based measure) and -0.111 (income-based measure) for the whole sample (Table 2.5), -0.089 (income-based measure) for the European sample (Table 2.6), and -0.096 (income-based measure) for the industrialised sample (Table 2.7). We also confirm the finding of a negative type effect which means that investment banks are more highly valued than commercial banks. In the first period, we find highly significant coefficient estimates of respectively -0.157 (asset-based measure) and -0.214 (income-based measure) for the whole sample, -0.107 and -0.169 for the European sample, and -0.130 and -0.146 for the industrialised sample.

The graphs displaying the combined effect in the left column of Figures 2.4 and 2.5 indicate that the slope is clearly negative in the range of interest-income share (or net loans share) of 0.0 to 0.5 and almost flat between 0.5 and 1.0. The combined line suggests that the type and diversification effects are driven by banks with a major investment banking profile (interest-income share or net loans share between 0.0 and 0.5). The number of these banks is small compared to the number of banks with a major commercial banking profile (interest-income share or net loans share between 0.5 and 1.0). Among the commercial banks, Tobin's Q is not systematically related to the share of investment banking activities. As long as the investment banking activities are not predominant, they are not rewarded by a valuation premium.

After the first period, the diversification discount drops substantially. Based on the income-based measure, it is still significant in the second and third period (2003-2006 and 2007-2009, respectively), but the magnitude of the coefficient is substantially lower compared to the first period. The coefficient estimate drops in absolute terms from -0.111 in the fist period to -0.050 in the second period and -0.061 in the third period in the whole sample, and from -0.096 in the first period to -0.073 in the second period and to -0.064 in the third period in the industrialised sample. The exception is the European sample that sees an increase in absolute terms from -0.089 in the first period to -0.120 in the second period and -0.103 in the third period. In the fourth period, diversification remains significantly negative in the sample of banks in industrialised countries (-0.044). It is no longer statistically significant in the European and in the whole samples. Based on the asset-based measure, the diversification coefficient is never significant (statistically or economically) after the first period (except in the fourth period for the whole sample where it is weakly significant).

The type effect also decreases substantially over time. In the whole sample, for example, the diversification discount drops from -0.214 in the first period, to -0.048 in the second period and to -0.073 in the third period. Banks in the European sample and in the sample of industrialised countries also show a substantial decrease in the type effect over time, both in terms of magnitude and statistical significance. A similar decrease is observed when using the asset-based measure. At a glance, this decline of type and diversification effects is apparent from Figures 2.4 and 2.5 which show flatter lines in later periods.

We test the hypothesis that the difference between the type and diversification coefficients in different time periods is equal to zero using the following formula: $Z = \dfrac{b_1 - b_2}{\sqrt{SEb_1^2 + SEb_2^2}}$, where the b's represent coefficient estimates, 1 and 2 relate to the different time periods, and the SE's are the standard errors of the respective slops. The difference between the type coefficient estimates in the first and in the fourth period is highly significant both for the asset-based measure ($Z = -2.6$, $p = 0.0094$) and the income-based measure ($Z = -3.57$, $p = 0.0004$). For Diversification, the difference in coefficient estimates is also statistically significant for the income-based measure ($Z = -2.46$, $p = 0.0140$), but not for the asset-based measure ($Z = -1.5$, $p = 0.1329$). Thus, most of the tests conclude that the coefficients are different in the first period, in which they are statistically significant, and in the fourth period, in which their respective effects practically vanish.

The most important control variable is operating profit. Its positive effect on Tobin's Q is in line with theoretical expectations. The results for the other control variables are less conclusive, with differences across periods and samples.

2.5. Robustness tests and endogeneity

In our baseline specification, Tobin's Q was winsorised at 1% and 99%. We obtain practically the same results when trimming (instead of winsorising) the observations below 1% and above 99%.[10] The results are also very similar when Tobin's Q is replaced by the market-to-book ratio of equity. The specific set of control variables also does not seem to be crucial. We run estimations for a reduced set of explanatory variables including only operating profit, log assets and country and time fixed effects and obtain the same main results for type and diversification.

Sample selection in the sense of Heckman (1979) should not be an issue because we use the entire sample of listed banks. However, there is some concern that type and diversification might be choice variables which are correlated with unobservables contained in the error term. Such a self-selection will produce an endogeneity bias which should be avoided by using instruments for the endogeneous variables. However, it is almost impossible to find appropriate instrumental variables. While variables proposed in the literature such as lagged diversification are correlated with diversification as required, they might well be correlated with the error term in the explanatory equation and thus suffer from the same problem as the diversification variable itself. Nevertheless, as a robustness check, we estimate the type and diversification effects with two instrumental variables proposed by Laeven and Levine (2007) (activity restriction in the country of origin, and diversification of other banks in the same country) and lagged diversification which is proposed by Elsas et al. (2010). The main conclusions remain valid. More specifically, we are able to replicate the results of Laeven and Levine (2007) for their period under study. For the other time periods, we confirm a weakening of the type and diversification effects over time for our three samples.

Another concern is that the results might be driven by a small number of highly valued investment banks. To examine this issue, Figures 2.6 and 2.7 show partial residual plots for the effect of interest-income share and net loans share on Tobin's Q. The graphs are the same as in Figures 2.4 and 2.5, but with residuals included. We also include an additional smooth nonparametric regression line based on a locally-weighted polynomial regression (LOWESS). This method does

[10] Unless indicated otherwise, results for this section are reported in Appendix A.

not make an assumption on the form of the regression, and it is less sensitive to outliers than a linear OLS regression. A further advantage of the LOWESS regression is that the position of a possible kink in the profile is extracted from the data rather than fixed in advance at a level of 0.5 as in the estimation approach so far.

[**Figure 2.6 about here**]

[**Figure 2.7 about here**]

A first interesting finding is that the LOWESS line can actually be approximated by a kinked linear profile with a kink at 0.5. This is consistent with the view that the relevant transition point is indeed 0.5 where the highest degree of diversification is achieved. The second important observation is that the magnitudes of the type effect and the diversification effect are almost always smaller compared to the standard regression. This is particularly true in the first period, where the strong type and diversification effects apparent in the standard regressions for asset- and income-based measures diminish considerably (to about half the effects or less). This finding is consistent with the hypothesis that the diversification discount found in the first period is partly due to a few rather extreme observations for investment banks that could be regarded as outliers. There is one noteworthy exception from the general observation that the LOWESS estimates of diversification effects are much smaller: for the European sample in the periods 2003-2006 and 2007-2009, the LOWESS regression is almost identical with the standard regression, which confirms the finding of a significant diversification discount in these periods. However, this discount is specific to the income-based measures (Fig. 2.6). For asset-based measures, the LOWESS regressions never show a pronounced diversification premium or discount. They suggest that only a small type effect (in favour of investment banks) exists (see Fig. 2.7).

2.6. Conclusion

In this paper, we aim to shed light on the conflicting results of prior studies on diversification effects in bank valuation. We argue that some of these results are not directly comparable to each other because the prior studies use different methodological frameworks in terms of estimation approach, proxy variables for diversification and control variables. The commonly used diversification measures are intimately associated with bank type because both variables are defined as a function of interest-income share. The diversification effect, by construction, has a symmetrical triangular structure (V-shape or inverted V-shape) because the effect is strongest for interest-income share of 0.5, and falls off towards investment banks (share of 0) and commercial banks (share of 1). When bank type is also relevant for valuation, there is a second effect running monotonically from an interest-income share of 0 (pure investment banks) to a level of 1 (pure commercial banks). It is not possible to identify the first effect without taking the second into account. However, bank type is not always included in prior studies. We show that this problem is important enough to explain the different results.

In a nutshell, our analysis yields the following results. In the first subperiod (1998-2002), we find a significant premium for investment banks and a significant diversification discount. However, this result is partly driven by a small number of large observations for investment banks, which is why the effects are considerably smaller in a robust regression. The diversification discount declines during the years before the financial crisis and practically vanishes in the last subperiod (2010-2013). Compared to previous studies, we observe more important differences between income-based and asset-based measures of diversification. For asset-based measures, we find no evidence of diversification effects outside the first subperiod. The results are similar for US and European banks and across regulatory regimes.

Figure 2.1: Bank type and diversification proxies

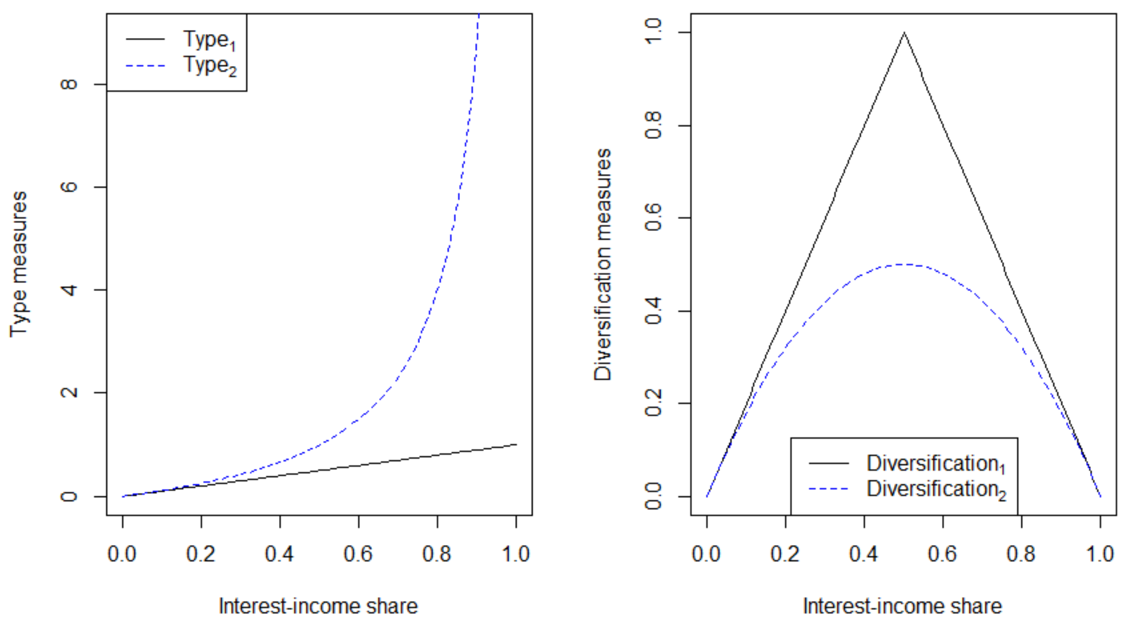


Figure 2.2: Tobin's Q and interest-income share in prior studies

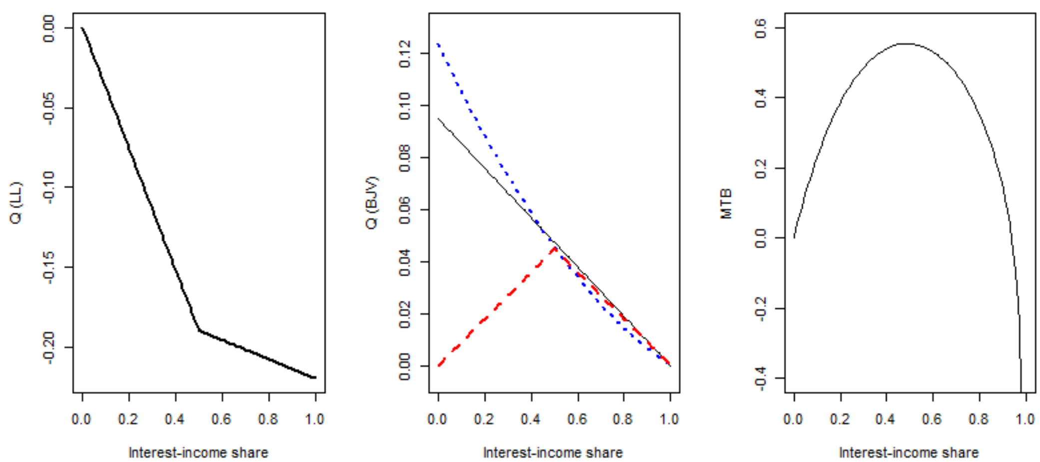


Table 2.1: Description and source of variables

Variable	Description and source
Tobin's Q	Ratio of the market value of equity plus the book value of liabilities to the book value of assets. Bankscope, Datastream
Type (assets)	Ratio of loans to total earning assets. Bankscope
Diversification (assets)	One minus the absolute value of the ratio of net loans minus other earning assets divided by total earning assets. Bankscope
Type (income)	Ratio of net interest income to total operating income. Bankscope
Diversification (income)	One minus the absolute value of the ratio of net interest income minus other operating income divided by total operating income. Bankscope
Deposit share	Ratio of customer deposits to total liabilities. Bankscope
Wholesale share	Ratio of wholesale funding, defined as total short-term funding minus customer deposits, to total liabilities. Bankscope
Operating profit	Ratio of operating profit to total assets. Bankscope
Cost-to-income	Ratio of overheads divided by the sum of net interest revenue plus other operating income. Bankscope
Loan loss provisions	Ratio of loan loss provisions to net loans. Bankscope
Z-score	Return on assets plus capital ratio divided by the standard deviation of the return on assets. Bankscope
Growth of total assets	This compares the current year's growth in total assets as a percentage of the previous year's total assets. Bankscope
Log assets	Natural logarithm of total assets. Bankscope
Equity	Ratio of common equity to total assets. Bankscope
Inflation	Consumer price inflation rate. World Bank
GDP growth	Growth rate of real per capita gross domestic product (GDP). World Bank
GDP per capita	GDP per capita in thousands of 2000 constant US dollars. World Bank
Capital regulation	Index of capital regulatory oversight of bank, with higher values indicating greater stringency. Barth, Caprio, and Levine (2013)
Diversification guidelines	Index of asset diversification guidelines imposed on banks, ranging from zero to two, with higher values indicating more diversification. Barth, Caprio, and Levine (2013)
Regulatory restrictions	Index of regulatory restrictions on bank activities, with higher values indicating more restrictive. Barth, Caprio, and Levine (2013)
Conglomerates restrictiveness	Index of overall financial conglomerates restrictiveness, with higher values indicating more restrictive. Barth, Caprio, and Levine (2013)
Statement transparency	The transparency of bank financial statement practices, with higher values indicating better transparency. Barth, Caprio, and Levine (2013)
Deposit insurance	Whether (0-1) there is an explicit deposit insurance scheme, with one indicating no such scheme. Barth, Caprio, and Levine (2013)
Supervisory power	Index of power of commercial bank supervisory agency, measuring the power of the supervisory authorities to take specific actions to prevent and correct problems, with higher values indicating greater power. Barth, Caprio, and Levine (2013)
Financial freedom	Index of financial freedom, scaled from zero to one hundred, with higher values indicating greater freedom. Heritage Foundation

Table 2.2: Descriptive statistics

	Obs.	Mean	S.D.	Min.	Max.
Tobin's q	19,677	1.04	0.15	0.70	2.69
Type (assets)	19,677	0.68	0.19	0.00	1.00
Diversification (assets)	19,677	0.53	0.25	0.00	1.00
Type (income)	19,677	0.70	0.20	0.00	1.00
Diversification (income)	19,677	0.48	0.26	0.00	1.00
Deposit share	19,677	0.77	0.22	0.00	1.00
Wholesale share	19,677	0.14	0.23	0.00	1.00
Operating profit	19,677	0.01	0.03	-0.99	2.27
Cost-to-income	19,677	65.56	33.14	1.48	960.99
Loan loss provisions	19,677	0.01	0.45	-21.13	53.27
Z-Score	19,677	0.67	4.65	-5.21	415.52
Growth in assets	19,677	11.50	26.90	-99.11	923.79
Log assets	19,677	15.02	2.10	11.51	22.06
Equity	19,677	0.10	0.09	-2.43	0.99
GDP growth	19,677	1.51	2.92	-16.59	16.20
GDP	19,677	37.85	18.11	0.74	133.73
Inflation	19,677	3.21	3.93	-4.86	74.30
Capital regulation	19,677	6.43	1.57	2.00	10.00
Activities restrictions	19,677	7.83	1.61	3.00	12.00
Conglomerate restrictiveness	19,677	7.69	1.58	3.00	12.00
Supervisory power	19,677	12.16	2.04	4.00	16.00
Diversification guidelines	19,677	1.42	0.57	0.00	2.00
No deposit insurance	19,677	0.12	0.33	0.00	1.00
Statement transparency	19,677	5.21	0.70	1.50	6.00
Financial freedom	19,677	67.12	18.63	10.00	90.00

GDP in thousands USD; Z-score in 1000000 thousands, Cost-to-income in thousands; Growth in assets in thousands.

Table 2.3: Country-specific descriptive statistics

	Obs.	Tobin's q	Type assets	Div. assets	Type income	Div. income	Log assets	Equity
Australia	84	1.04	0.79	0.39	0.69	0.52	17.75	0.06
Austria	125	0.97	0.63	0.72	0.66	0.61	16.92	0.07
Bahrain	118	1.07	0.42	0.56	0.48	0.47	14.93	0.18
Bangladesh	53	1.03	0.76	0.48	0.65	0.65	14.36	0.08
Belgium	29	1.01	0.37	0.67	0.66	0.65	18.34	0.07
Belize	7	0.87	0.78	0.43	0.69	0.63	13.72	0.28
Benin	6	0.99	0.51	0.89	0.67	0.66	13.82	0.09
Bosnia Herz.	19	1.05	0.85	0.31	0.67	0.63	12.88	0.11
Botswana	18	1.36	0.65	0.63	0.68	0.64	14.05	0.20
Brazil	234	0.96	0.45	0.66	0.74	0.44	15.56	0.13
Bulgaria	42	1.11	0.70	0.58	0.61	0.73	13.95	0.12
Canada	38	1.02	0.69	0.57	0.60	0.61	17.89	0.07
Chile	53	1.06	0.78	0.45	0.61	0.68	16.38	0.08
China	106	1.01	0.50	0.89	0.85	0.30	19.47	0.06
Colombia	104	1.02	0.74	0.50	0.52	0.73	15.62	0.09
Ivory Coast	6	1.04	0.74	0.52	0.41	0.83	13.60	0.12
Croatia	149	1.00	0.69	0.60	0.66	0.67	13.91	0.12
Cyprus	58	1.05	0.66	0.68	0.68	0.62	15.62	0.05
Czech Rep.	38	1.04	0.46	0.80	0.62	0.76	16.56	0.07
Denmark	437	1.01	0.68	0.60	0.69	0.60	13.74	0.11
Ecuador	45	1.06	0.66	0.65	0.54	0.74	13.67	0.09
Egypt	128	1.09	0.47	0.76	0.60	0.60	14.70	0.12
Estonia	24	1.10	0.77	0.45	0.60	0.78	15.19	0.10
Finland	26	1.02	0.57	0.64	0.39	0.63	16.51	0.06
France	437	0.99	0.63	0.43	0.52	0.61	15.86	0.11
Gambia	6	1.30	0.43	0.82	0.50	0.94	11.74	0.09
Georgia	3	0.94	0.79	0.43	0.56	0.88	15.01	0.17
Germany	309	1.03	0.49	0.56	0.60	0.51	17.17	0.07
Ghana	33	1.13	0.57	0.70	0.66	0.67	13.47	0.14
Greece	107	1.05	0.67	0.49	0.71	0.49	16.89	0.07
Honk Kong	112	1.06	0.59	0.76	0.69	0.59	16.61	0.13
Hungary	34	1.05	0.69	0.54	0.65	0.67	15.34	0.08

Table 2.3: Country-specific descriptive statistics (continued)

	Obs.	Tobin's q	Type assets	Div. assets	Type income	Div. income	Log assets	Equity
Iceland	20	1.46	0.56	0.57	0.57	0.61	16.06	−0.42
India	520	1.05	0.66	0.64	0.65	0.57	15.74	0.08
Indonesia	317	1.09	0.60	0.61	0.75	0.39	14.69	0.11
Ireland	35	1.02	0.64	0.62	0.82	0.36	18.55	0.04
Israel	136	0.99	0.74	0.47	0.61	0.75	16.33	0.06
Italy	318	1.02	0.67	0.48	0.60	0.63	16.65	0.10
Japan	1,780	1.00	0.69	0.58	0.76	0.32	17.00	0.06
Jordan	117	1.07	0.55	0.81	0.68	0.60	14.59	0.14
Kazakhstan	63	1.06	0.84	0.31	0.71	0.55	15.00	0.11
Kenya	120	1.15	0.68	0.59	0.64	0.70	13.64	0.13
Kuwait	159	1.21	0.41	0.46	0.40	0.37	14.89	0.29
Latvia	13	0.98	0.79	0.43	0.61	0.60	14.56	0.07
Lebanon	65	0.97	0.32	0.64	0.70	0.59	15.40	0.06
Lithuania	60	1.09	0.72	0.50	0.58	0.71	14.22	0.09
Luxembourg	45	1.01	0.40	0.62	0.40	0.60	16.85	0.08
Macedonia	21	0.95	0.85	0.31	0.70	0.59	12.75	0.13
Malawi	7	1.10	0.74	0.50	0.60	0.78	12.71	0.15
Malaysia	83	0.98	0.56	0.51	0.50	0.58	15.34	0.24
Malta	41	1.09	0.48	0.65	0.57	0.66	14.73	0.11
Mauritius	5	1.11	0.63	0.74	0.68	0.64	14.83	0.16
Mexico	135	1.26	0.57	0.65	0.62	0.62	16.32	0.14
Montenegro	18	1.12	0.82	0.36	0.73	0.54	12.96	0.11
Morocco	64	1.11	0.77	0.33	0.77	0.41	14.88	0.11
Namibia	9	1.10	0.80	0.39	0.57	0.85	14.47	0.12
Netherlands	71	1.09	0.49	0.64	0.52	0.55	17.43	0.06
New Zealand	1	1.00	0.96	0.08	0.20	0.41	12.64	0.09
Nigeria	50	1.03	0.53	0.82	0.66	0.65	15.66	0.08
Norway	209	0.96	0.82	0.29	0.71	0.49	15.27	0.07
Oman	75	1.12	0.78	0.38	0.75	0.48	14.56	0.17
Pakistan	105	1.01	0.59	0.74	0.62	0.48	13.55	0.10
Panama	16	0.95	0.75	0.49	0.77	0.46	15.27	0.12

Table 2.3: Country-specific descriptive statistics (continued)

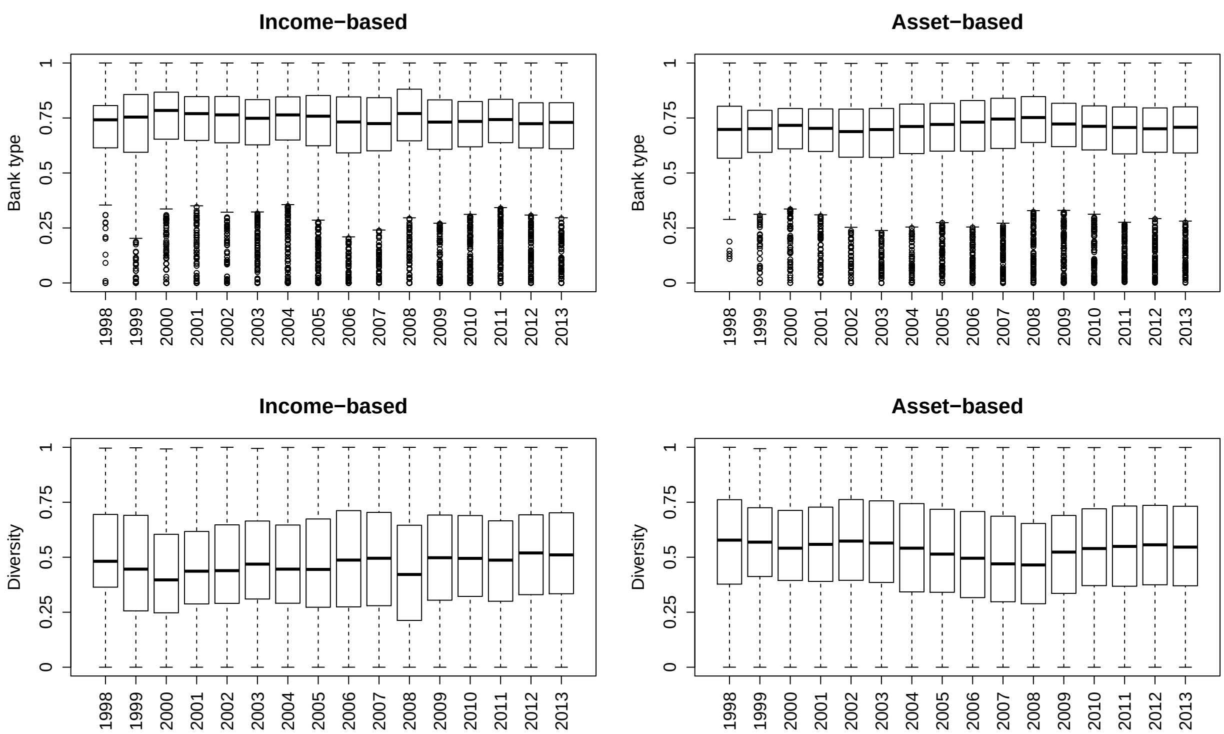
	Obs.	Tobin's q	Type assets	Div. assets	Type income	Div. income	Log assets	Equity
Peru	119	1.04	0.78	0.44	0.75	0.46	14.15	0.11
Philippines	136	1.05	0.48	0.74	0.61	0.70	14.93	0.13
Poland	143	1.11	0.68	0.57	0.56	0.82	16.12	0.10
Portugal	61	1.06	0.75	0.47	0.62	0.73	16.93	0.07
Qatar	69	1.27	0.62	0.74	0.69	0.62	16.04	0.16
Korea	127	0.95	0.58	0.38	0.70	0.43	16.60	0.11
Romania	45	1.10	0.73	0.48	0.57	0.81	15.09	0.11
Russia	132	1.02	0.73	0.48	0.65	0.58	15.86	0.12
Saudi Arabia	117	1.28	0.62	0.73	0.68	0.62	16.73	0.13
Serbia	38	0.93	0.72	0.52	0.42	0.63	13.17	0.23
Singapore	69	0.98	0.68	0.61	0.73	0.51	15.96	0.16
Slovakia	42	0.97	0.64	0.62	0.71	0.57	15.39	0.07
Slovenia	46	0.99	0.72	0.56	0.63	0.69	14.82	0.08
South Africa	123	1.13	0.65	0.47	0.45	0.76	15.71	0.17
Spain	103	1.02	0.73	0.49	0.65	0.67	17.99	0.06
Sri Lanka	36	1.02	0.75	0.49	0.72	0.49	13.38	0.12
Sweden	61	1.05	0.53	0.59	0.47	0.65	17.43	0.05
Switzerland	378	1.03	0.67	0.35	0.53	0.55	16.12	0.10
Thailand	281	1.03	0.68	0.52	0.57	0.54	15.12	0.18
Togo	5	0.96	0.62	0.77	0.51	0.96	16.51	0.11
Tunisia	156	1.02	0.82	0.35	0.70	0.55	13.71	0.13
Turkey	185	1.05	0.71	0.56	0.75	0.46	15.74	0.14
Uganda	15	1.21	0.59	0.81	0.73	0.54	13.06	0.14
Ukraine	28	1.06	0.87	0.25	0.71	0.57	14.46	0.13
United Arab Em.	181	1.15	0.68	0.53	0.63	0.60	15.53	0.19
United Kingdom	177	1.07	0.60	0.51	0.57	0.57	17.75	0.10
United States	8,890	1.03	0.73	0.51	0.77	0.42	14.06	0.09
Venezuela	168	1.02	0.66	0.62	0.71	0.54	15.01	0.10
Vietnam	45	1.06	0.60	0.77	0.74	0.39	15.71	0.09
Zambia	12	1.15	0.59	0.80	0.55	0.85	13.25	0.09
Zimbabwe	23	1.01	0.82	0.35	0.36	0.61	12.62	0.14

Table 2.4: Correlation matrix

	Diversification (assets)	Type (income)	Diversification (income)
Type (assets)	-0.479^{***}	0.392^{***}	-0.018^{**}
	(0.00)	(0.00)	(0.01)
Div. (assets)	1.000	-0.003	0.138^{***}
		(0.72)	(0.00)
Type (income)		1.000	-0.447^{***}
			(0.00)
Div. (income)			1.000

Pearson correlation coefficients. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Figure 2.3: Evolution of distributional characteristics of bank type and diversification over time



The boxplots illustrate the evolution of bank type (upper graphs) and diversification (lower graphs) over time for income- and asset-based measures within the whole sample.

Table 2.5: Regression results - Whole sample

	1998-2002	2003-2006	2007-2009	2010-2013	1998-2002	2003-2006	2007-2009	2010-2013
	Asset-based measures				Income-based measures			
Type	-0.157^{***}	-0.049^{**}	-0.069^{**}	-0.010	-0.214^{***}	-0.048^{*}	-0.073^{**}	-0.007
	(0.00)	(0.02)	(0.04)	(0.66)	(0.00)	(0.06)	(0.02)	(0.79)
Diversification	-0.071^{**}	0.015	0.019	-0.022^{*}	-0.111^{***}	-0.050^{***}	-0.061^{***}	-0.018
	(0.02)	(0.41)	(0.34)	(0.10)	(0.00)	(0.00)	(0.00)	(0.21)
Deposit share	-0.001	0.045^{**}	0.052^{**}	-0.021	0.018	0.051^{**}	0.062^{***}	-0.021
	(0.99)	(0.03)	(0.02)	(0.26)	(0.66)	(0.02)	(0.01)	(0.27)
Wholesale share	-0.016	0.049^{***}	0.060^{**}	-0.019	-0.066	0.035^{*}	0.043^{*}	-0.016
	(0.69)	(0.01)	(0.02)	(0.22)	(0.16)	(0.06)	(0.07)	(0.30)
Operating profit	1.167	3.383^{***}	0.511^{*}	0.545^{**}	1.156	3.236^{***}	0.491	0.546^{**}
	(0.16)	(0.00)	(0.09)	(0.04)	(0.13)	(0.00)	(0.10)	(0.04)
Cost-to-income	0.063	0.154	-0.056	0.166	-0.125	0.147	-0.073	0.162
	(0.76)	(0.22)	(0.66)	(0.47)	(0.54)	(0.28)	(0.57)	(0.49)
Loan loss provisions	0.004	-0.005	0.005	-0.080^{*}	0.007	-0.006	0.005	-0.080
	(0.70)	(0.66)	(0.12)	(0.10)	(0.41)	(0.52)	(0.11)	(0.10)
Z-Score	-0.015^{**}	-0.002^{*}	0.000	0.000	-0.012^{**}	-0.001	0.001	0.000
	(0.01)	(0.05)	(0.84)	(0.96)	(0.02)	(0.17)	(0.29)	(0.99)
Growth in assets	0.248^{*}	0.321^{**}	0.199	0.266^{*}	0.184	0.278^{**}	0.188	0.276^{*}
	(0.08)	(0.02)	(0.29)	(0.07)	(0.18)	(0.04)	(0.34)	(0.06)
Log assets	0.009^{**}	-0.004^{**}	-0.008^{***}	0.003^{*}	0.010^{**}	-0.002	-0.005^{*}	0.003^{*}
	(0.03)	(0.05)	(0.01)	(0.08)	(0.01)	(0.35)	(0.07)	(0.07)
Equity	0.142	-0.056	-0.100	0.053	0.168	-0.052	-0.122	0.051
	(0.47)	(0.47)	(0.44)	(0.50)	(0.39)	(0.51)	(0.33)	(0.52)
Observations	3421	5171	4490	6595	3421	5171	4490	6595
R-squared	0.174	0.362	0.246	0.294	0.205	0.362	0.247	0.294
Macroeconomic control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regulatory control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

The dependent variable is Tobin's Q. Macroeconomic and regulatory control variables are included in the estimation but the coefficients are not reported. The macroeconomic control variables are inflation, GDP growth rate and GDP per capita. Regulatory control variables used are capital stringency, diversification guidelines, restrictions on bank activities, financial conglomerates restrictiveness, financial statement transparency, presence of explicit deposit insurance scheme, supervisory power, and an index of financial freedom. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. p-values in parentheses.

Table 2.6: Regression results - European sample

	1998-2002	2003-2006	2007-2009	2010-2013	1998-2002	2003-2006	2007-2009	2010-2013
	Asset-based measures				Income-based measures			
Type	-0.107^{*}	-0.117^{***}	-0.063^{**}	-0.081^{**}	-0.169^{***}	-0.046	-0.043	-0.052^{*}
	(0.07)	(0.00)	(0.01)	(0.02)	(0.00)	(0.18)	(0.27)	(0.10)
Diversification	-0.035	-0.001	0.024	-0.024	-0.089^{**}	-0.120^{***}	-0.103^{***}	-0.043
	(0.40)	(0.98)	(0.41)	(0.44)	(0.04)	(0.00)	(0.00)	(0.13)
Deposit share	0.015	0.011	0.073	0.053	0.028	0.037	0.083^{*}	0.038
	(0.79)	(0.76)	(0.16)	(0.14)	(0.61)	(0.34)	(0.10)	(0.30)
Wholesale share	-0.057	0.067	0.041	0.054	-0.028	0.050	0.026	0.042
	(0.24)	(0.11)	(0.33)	(0.18)	(0.57)	(0.20)	(0.51)	(0.30)
Operating profit	3.665^{***}	3.155^{***}	1.141	1.207^{**}	3.528^{***}	2.827^{***}	1.034	1.341^{***}
	(0.00)	(0.00)	(0.11)	(0.01)	(0.00)	(0.00)	(0.13)	(0.01)
Cost-to-income	0.791^{**}	0.837^{***}	0.126	0.131	0.744^{***}	0.838^{**}	0.069	0.237
	(0.03)	(0.01)	(0.47)	(0.33)	(0.01)	(0.01)	(0.68)	(0.14)
Loan loss provisions	0.007	-0.008	0.009	0.038	0.012^{*}	-0.005	0.008	0.057^{*}
	(0.35)	(0.59)	(0.13)	(0.29)	(0.09)	(0.71)	(0.18)	(0.10)
Z-Score	-0.004	0.001	0.002^{**}	0.000	-0.007	0.001	0.003^{***}	0.001
	(0.71)	(0.56)	(0.05)	(0.64)	(0.47)	(0.21)	(0.00)	(0.25)
Growth in assets	0.171	0.233	-0.245	-0.658	0.115	0.236	-0.215	-0.591
	(0.41)	(0.12)	(0.31)	(0.27)	(0.53)	(0.13)	(0.35)	(0.35)
Log assets	-0.003	-0.017^{***}	-0.014^{***}	-0.009^{*}	-0.002	-0.010^{*}	-0.011^{**}	-0.009^{**}
	(0.72)	(0.00)	(0.01)	(0.05)	(0.84)	(0.06)	(0.02)	(0.04)
Equity	0.617^{*}	-0.094	-0.119	-0.299^{**}	0.520^{*}	0.007	-0.126	-0.329^{**}
	(0.06)	(0.56)	(0.44)	(0.04)	(0.08)	(0.97)	(0.36)	(0.02)
Observations	428	636	819	1045	428	636	819	1045
R-squared	0.522	0.464	0.232	0.197	0.554	0.485	0.266	0.187
Macroeconomic control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regulatory control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

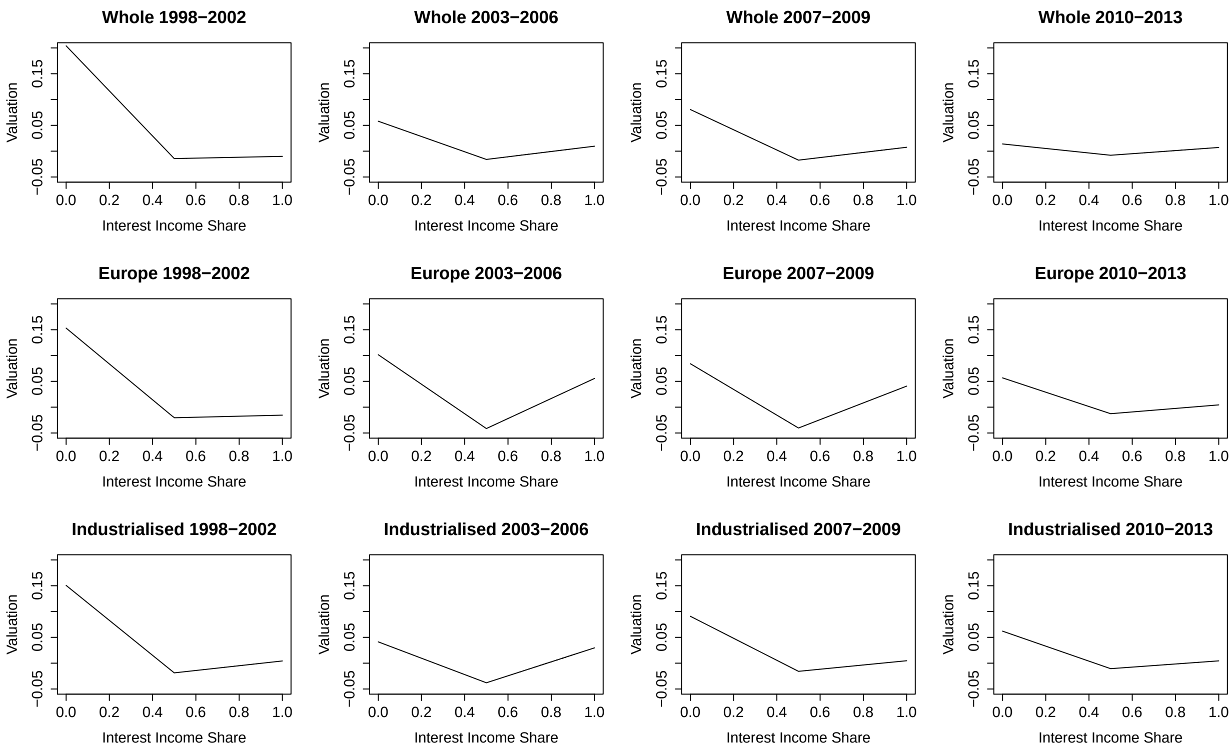
The dependent variable is Tobin's Q. Macroeconomic and regulatory control variables are included in the estimation but the coefficients are not reported. The macroeconomic control variables are inflation, GDP growth rate and GDP per capita. Regulatory control variables used are capital stringency, diversification guidelines, restrictions on bank activities, financial conglomerates restrictiveness, financial statement transparency, presence of explicit deposit insurance scheme, supervisory power, and an index of financial freedom. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. p-values in parentheses.

Table 2.7: Regression results - Industrialised countries sample

	1998-2002	2003-2006	2007-2009	2010-2013	1998-2002	2003-2006	2007-2009	2010-2013
	Asset-based measures				Income-based measures			
Type	-0.130^{***}	-0.085^{***}	-0.089^{***}	-0.058^{***}	-0.146^{***}	-0.012	-0.086^{**}	-0.058^{**}
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.69)	(0.02)	(0.03)
Diversification	-0.039^{*}	0.019	0.029	-0.002	-0.096^{***}	-0.073^{***}	-0.064^{***}	-0.044^{***}
	(0.09)	(0.34)	(0.20)	(0.87)	(0.00)	(0.00)	(0.00)	(0.01)
Deposit share	0.012	0.060^{**}	0.109^{***}	0.056^{*}	0.023	0.056^{**}	0.104^{***}	0.056^{**}
	(0.71)	(0.02)	(0.00)	(0.05)	(0.45)	(0.04)	(0.00)	(0.05)
Wholesale share	-0.014	-0.016	0.055	-0.009	-0.003	-0.012	0.039	-0.018
	(0.76)	(0.35)	(0.22)	(0.72)	(0.94)	(0.48)	(0.36)	(0.46)
Operating profit	4.933^{***}	5.168^{***}	0.986^{**}	0.327^{**}	4.770^{***}	5.237^{***}	1.056^{**}	0.342^{**}
	(0.00)	(0.00)	(0.04)	(0.04)	(0.00)	(0.00)	(0.03)	(0.05)
Cost-to-income	1.311^{***}	0.892^{***}	0.115	-0.234	1.188^{***}	1.162^{***}	0.130	-0.217
	(0.00)	(0.00)	(0.38)	(0.14)	(0.01)	(0.00)	(0.31)	(0.23)
Loan loss provisions	0.019^{*}	0.063^{***}	0.009^{***}	-0.078	0.022^{**}	0.045^{**}	0.009^{***}	-0.081
	(0.09)	(0.00)	(0.01)	(0.11)	(0.03)	(0.01)	(0.01)	(0.13)
Z-Score	-0.017^{***}	-0.002^{**}	0.000	-0.001^{**}	-0.016^{***}	-0.001	0.001	0.000
	(0.00)	(0.03)	(0.64)	(0.04)	(0.00)	(0.36)	(0.22)	(0.26)
Growth in assets	0.457^{***}	0.003	0.037	0.471^{***}	0.429^{***}	-0.084	0.037	0.497^{***}
	(0.00)	(0.97)	(0.88)	(0.00)	(0.01)	(0.23)	(0.89)	(0.00)
Log assets	0.014^{***}	-0.002	-0.004^{*}	0.002	0.014^{***}	0.003	-0.002	0.004^{**}
	(0.00)	(0.43)	(0.08)	(0.14)	(0.00)	(0.17)	(0.39)	(0.02)
Equity	0.794^{***}	0.047	-0.132	-0.014	0.754^{***}	0.075	-0.135	-0.041
	(0.00)	(0.69)	(0.36)	(0.84)	(0.00)	(0.55)	(0.31)	(0.55)
Observations	2111	3150	2311	3162	2111	3150	2311	3162
R-squared	0.486	0.182	0.151	0.139	0.493	0.178	0.141	0.141
Macroeconomic control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regulatory control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

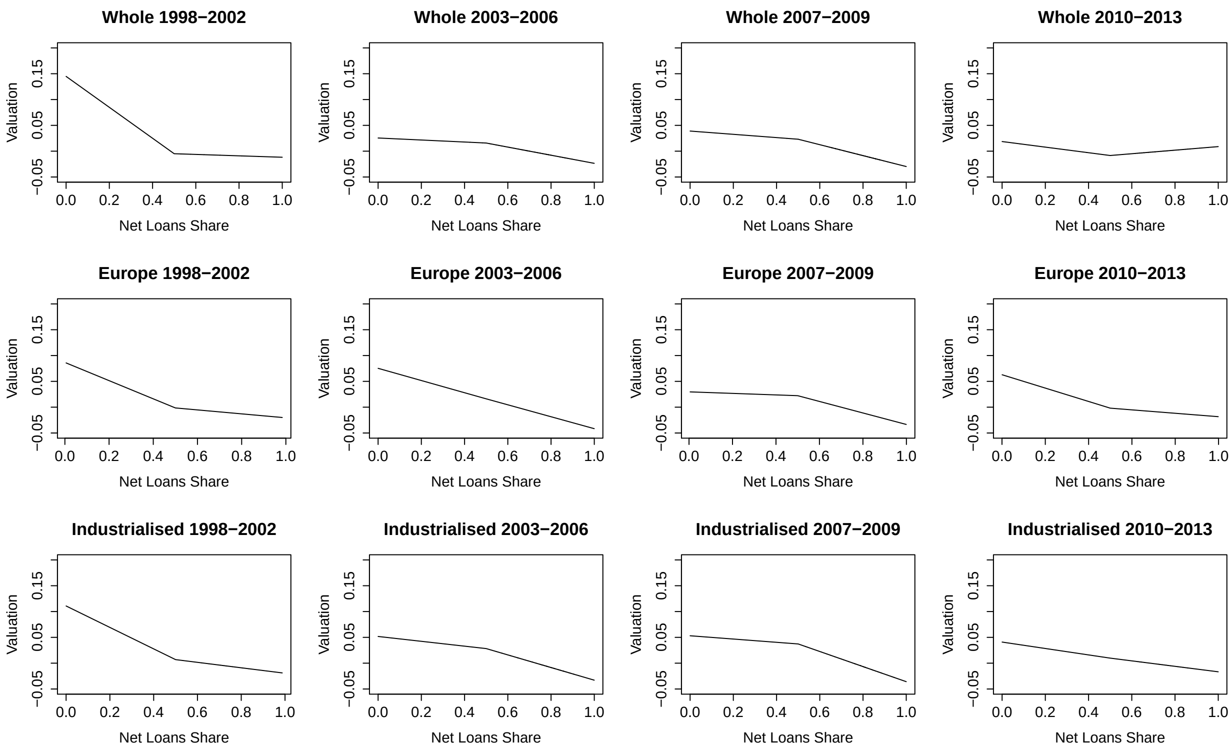
The dependent variable is Tobin's Q. Macroeconomic and regulatory control variables are included in the estimation but the coefficients are not reported. The macroeconomic control variables are inflation, GDP growth rate and GDP per capita. Regulatory control variables used are capital stringency, diversification guidelines, restrictions on bank activities, financial conglomerates restrictiveness, financial statement transparency, presence of explicit deposit insurance scheme, supervisory power, and an index of financial freedom. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. p-values in parentheses.

Figure 2.4: Net diversification effect (income)



The graphs show the partial response of Tobin's Q to interest-income share as implied in the regression coefficients of bank type and diversification. The other independent variables included in the model are bank-level, macroeconomic and regulatory control variables. "Whole" refers to the whole sample, "Europe" to the European sample, and "Industrialised" to the sample of 9 industrialised countries.

Figure 2.5: Net diversification effect (assets)



The graphs show the partial response of Tobin's Q to net loans share as implied in the regression coefficients of bank type and diversification. The other independent variables included in the model are bank-level, macroeconomic and regulatory control variables. "Whole" refers to the whole sample, "Europe" to the European sample, and "Industrialised" to the sample of 9 industrialised countries.

Figure 2.6: Partial residual plots (income)

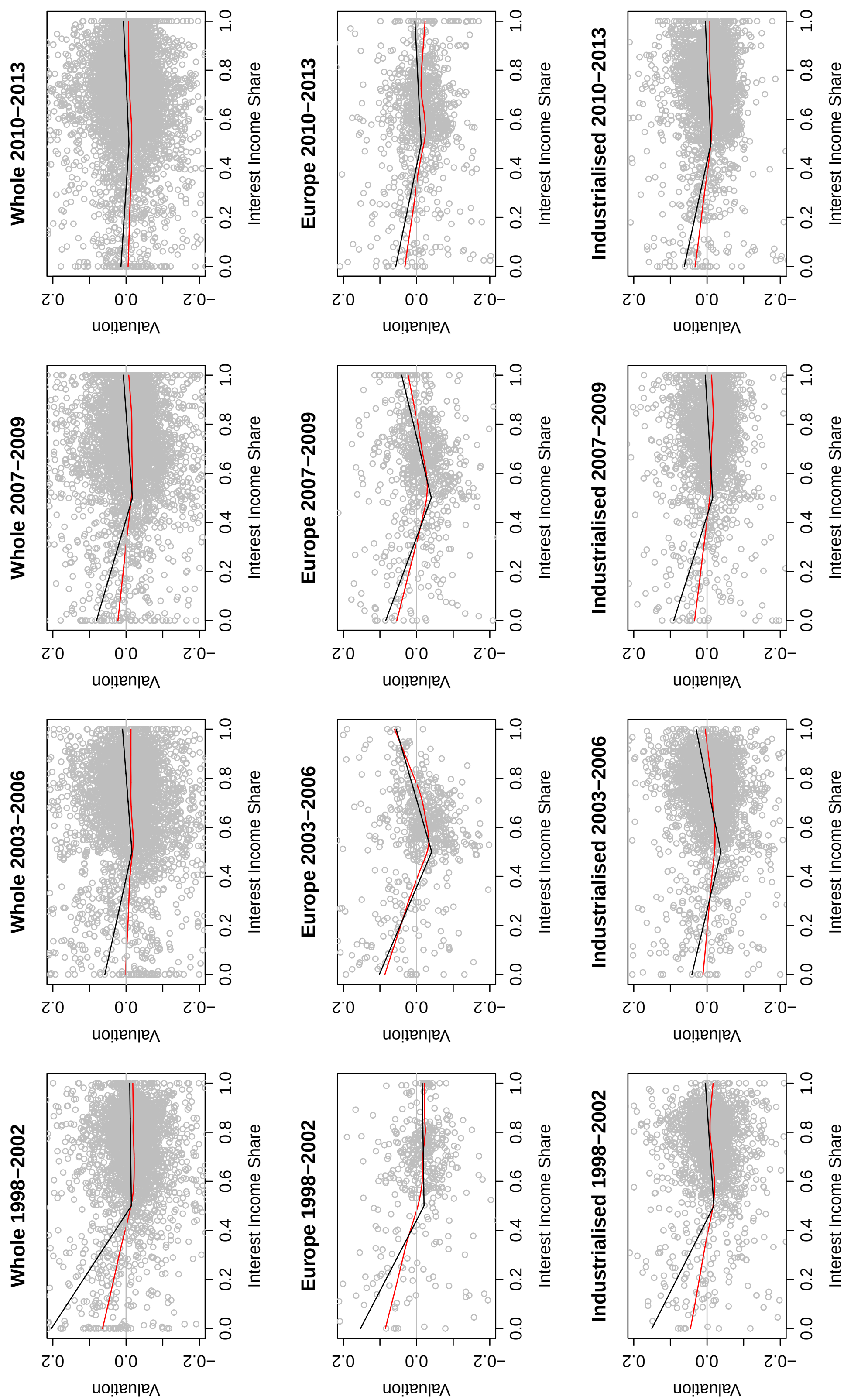
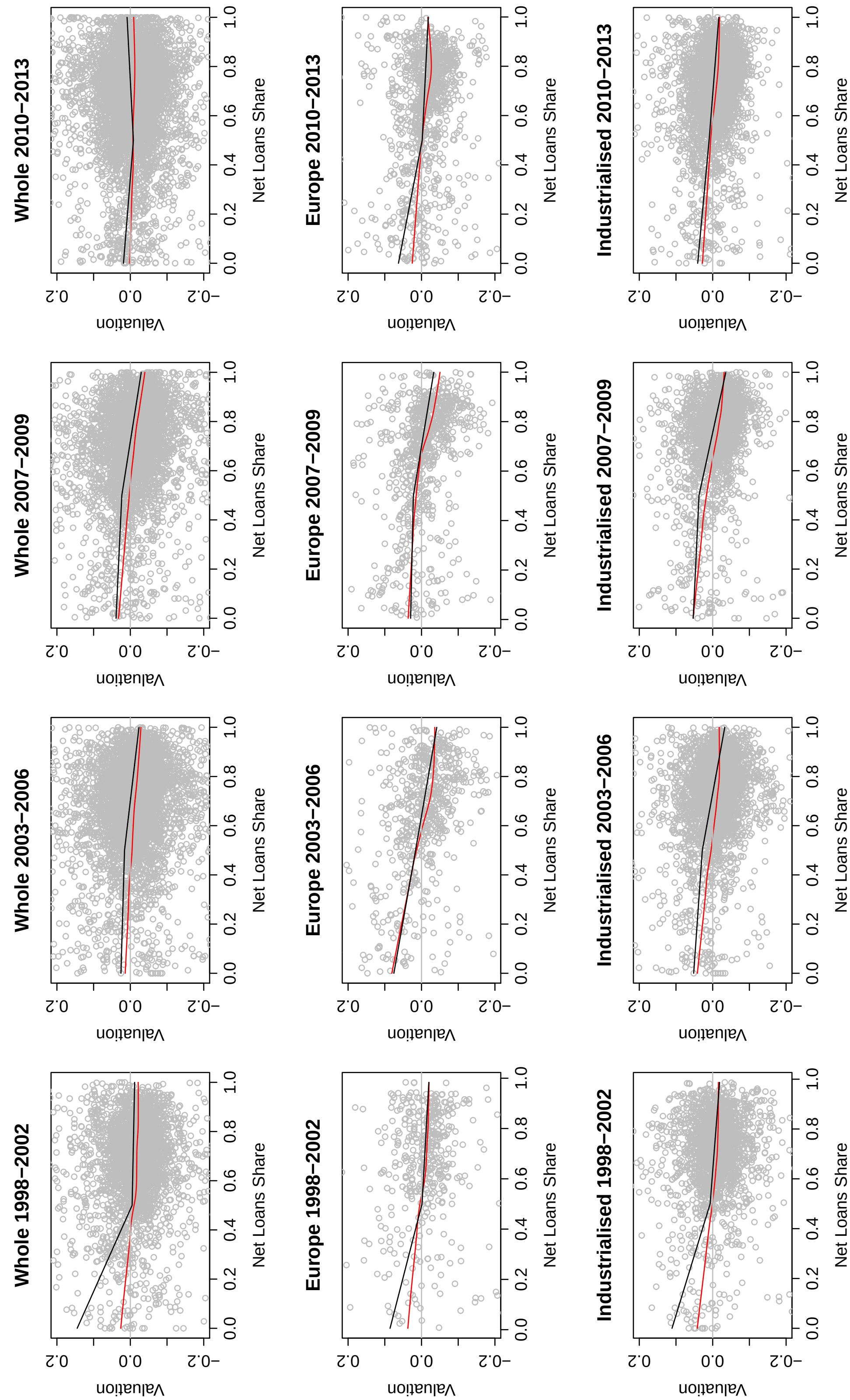


Figure 2.7: Partial residual plots (assets)



Chapter 3

Profitability and Other Industry-Specific Determinants of Banks' Cross-Sectional Returns

Profitability and Other Industry-Specific Determinants of Banks' Cross-Sectional Returns

Nicolas Guerry*

January 25, 2016

Abstract

This study investigates the predicting power of profitability and industry-specific variables on the cross-section of U.S. bank stock returns between 1980-2014. While the profitability premium has attracted growing attention in the past few years, its existence within the banking industry remains unknown since banks are typically excluded from asset pricing studies. Overall, our findings do not point at the existence of a strong profitability premium. However, we find convincing evidence suggesting that book-to-market and past performance at a horizon of one month (short-term return reversal), and several industry-specific variables such as loan loss provisions and asset mix composition can predict the cross-section of expected returns. Results regarding short-term return reversal are particularly strong in terms of statistical and economic significance.

Keywords: Asset pricing, Bank stock returns, Trading strategies, Profitability, Factor models.

JEL Classification Numbers: G12, G14, G21 .

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3.1. Introduction

The profitability premium that relates more profitable firms to higher stock returns had long been the least explored market anomaly (Sehgal, 2012). In the past few years, however, it has drawn particular interest from the academic literature. For example, Hou, Xue, and Zhang (in press) showed that profitability proxied by ROE can help explain a large set of asset pricing anomalies. Similarly, Novy-Marx (2013) showed that profitability proxied by gross profits-over-assets has roughly the same power as book-to-market in predicting expected returns. Moreover, Fama and French (2014) have extended their three-factor model to a five-factor model by including a profitability-based factor. These various contributions underline the growing importance of the profitability premium in the empirical literature.

Financial institutions are typically excluded from cross-sectional asset pricing studies because they are "different" from nonfinancial firms. Fundamental differences relate to the high leverage of financial institutions, their higher sensitivity to financial risk, and to the high level of regulation prevailing in this industry.[1] The exclusion of financial firms, making up a substantial fraction of domestic equity markets, from empirical studies creates a sizeable holdout sample since a large number of listed companies are not accounted for (Baek & Bilson, 2014; Barber & Lyon, 1997; Cooper et al., 2003; Viale et al., 2009). This exclusion also means that the existence of market anomalies among financial firms remains unclear. Financial institutions might therefore be characterised by other patterns explaining stock market returns compared to nonfinancial firms (Barber & Lyon, 1997; Cooper et al., 2003).

This study investigates the predicting power of profitability on the cross-section of expected stock returns in the U.S. banking industry between 1980-2014. It looks at the holdout sample created by the exclusion of financial institutions from the recent studies of Fama and French (2006, 2008) and Novy-Marx (2013). To the best of our knowledge, it is the first study to explore

[1] Fama and French (1992) excluded financial firms from their initial study on the cross-section of expected stock returns because of their initial interest in leverage as an explanatory variable for security returns (Barber & Lyon, 1997). As a result, subsequent studies relating to this topic have excluded financial firms as well. For more details on differences relating to leverage, see for example Fama and French (1992), Barber and Lyon (1997), or Viale et al. (2009); for financial risk, see Gandhi and Lustig (2013); and for regulation see Mishkin and Eakins (2012) or Cooper et al. (2003).

this particular market anomaly in the banking industry. In addition to profitability, we also explore the ability of industry-specific variables to predict the cross-section of returns. Cooper et al. (2003) investigated the relation between quarterly *changes* in several banking industry-specific variables and stock market returns in order to analyse the effect of *good/bad news shocks*, rather than predicting the determinants of expected cross-sectional returns. As underlined by the authors of the study, they used a different approach compared to traditional studies such as Fama and French (1992) or Lakonishok, Shleifer, and Vishny (1994), or this study, that examine the relation between expected returns and *levels* of fundamental variables. Finally, since we include control variables accounting for well-know market anomalies such as size, book-to-market, and past returns at different horizons, our study also provides fresh evidence about the predicting power of these anomalies in the banking industry. To the best of our knowledge, the impact of momentum on the cross-section of bank stock returns has never been investigated.

Our main results can be summarised as follows. We find mixed evidence regarding the predicting power of profitability. Evidence from Fama and MacBeth (1973) cross-sectional regression suggests a positive relationship between profitability and expected stock returns. However, further analysis shows that small market capitalisations are very influential in explaining this result; once the smallest market capitalisations are excluded from the analysis, the statistical significance of the relationship disappears. In addition, results from one-way sorts of returns on profitability are largely inconclusive and do not point to the existence of a market premium. Similarly, evidence indicating the presence of abnormal returns suggested by significant intercepts of long−short portfolios regressed on the four-factor model of Carhart (1997) are very limited. These results contrast with recent, clear-cut evidence from Novy-Marx (2013) suggesting that profitability is a strong predictor of expected cross-sectional returns. Thus, the profitability premium seems to be much more pronounced among nonfinancial firms than it is in the banking industry.

Second, among traditional market anomalies, we find evidence suggesting that book-to-market, size, and past performance at a horizon of one month can predict the cross-section of expected returns. Past performance at a horizon of one month, suggesting short-term return reversal, stands out from the other variables investigated in terms of economic and statistical significance. In the one-way sorts portfolios, we find an average monthly return of 2.079% for the long−short portfolio as well as a statistically significant intercept suggesting excess returns of 2.12% in time series regression. In Fama and MacBeth (1973) cross-sectional regression, the statistical significance of this variable stands out as well. Finally, we find the effect to be particularly stable over time and persistent in all portfolios sorted on size, meaning that this short-term return reversal does not result from high volume transactions among small, illiquid stocks. We also find convincing evidence regarding the predicting power of book-to-market. As for the predicting power of size, it appears to be, similar to profitability, largely driven by the smallest market capitalisations. Finally, our results do not suggest that past performance at a horizon of two to 12 months (momentum) can effectively predict expected stock returns.

And third, for industry-specific variables, our results show that loan loss provisions, loan share, and activity diversification can all predict the cross-section of expected stock returns. Banks with a lower ratio of loan loss provisions to total assets, a lower share of loans to total earnings assets, and a higher degree of assets diversification are associated with higher returns. We find convincing evidence in most of our tests (Fama and MacBeth (1973) regression, one-way sort portfolios, intercepts from time series regression). Finally, we find only limited evidence regarding the predicting power of deposit share, and none regarding the predicting power of equity.

The remainder of this paper is structured as follows. In Section 3.2, we review the relevant literature with special focus on market anomalies in banking, the profitability premium, and banking industry-specific variables as determinants of expected returns. In Section 3.3, we discuss the variables and the methodology used in the empirical part, while we present the data and the descriptive statistics in Section 3.4. Section 3.5 presents and discusses the results of the empirical analysis. In Section 3.6, we conduct and discuss several robustness tests of our results. Section 3.7 concludes.

3.2. Relevant literature

Market anomalies in banking

There is a lot of debate about whether market anomalies, i.e. patterns in average stock returns not explained by the CAPM, are due to market efficiency or market inefficiency. The first view is based on rational pricing and holds that market anomalies can be attributed to differences in risk. Controlling for other variables, this stream of the literature views firms with, say, higher book-to-market or lower market capitalisation, as riskier (e.g. higher cost of capital, greater business risk) than firms with lower book-to-market or larger market capitalisation. Consequently, investors require a higher rate of return as a compensation for this higher risk. The second view typically relates the higher returns of market anomalies to irrational pricing and argues that market participants misprice the value of these companies. This mispricing provides excess returns. Irrational pricing (e.g. price under- or overreaction) is the result of cognitive errors that investors make when incorporating information into prices. For example, investors may be too quick to draw the conclusion that a given stock follows a particular "ideal type", and they may be too slow to update their beliefs when confronted with new evidence (Fama & French, 2006; Haugen & Baker, 1996; Li, Miffre, & O'Sullivan, 2008).

Since banks are typically excluded from cross-sectional asset pricing studies, the existence of market anomalies remains largely unknown in this industry and limited to a few studies. Barber and Lyon (1997) were the first to exploit this holdout sample in order to look at the size and market-to-book anomaly in the financial industry. The authors analysed monthly cross-sectional returns of U.S. financial institutions between 1973-1994 by sorting firms on size and book-to-market value deciles (one-way sort portfolios) and compared the means of these deciles. Barber and Lyon (1997) found that financial firms, similar to nonfinancial firms, had significant size (small firm premium) and book-to-market premiums. Cooper et al. (2003) investigated the relationship between quarterly changes in several bank-level fundamental variables and the cross-section of stock market returns for a sample of U.S. banks between 1986-1999. They used one-way sort portfolios and Fama and MacBeth (1973) cross-sectional regressions. Relevant for market anomalies, they controlled for size and book-to-market by including levels of these two variables. They did not find any significant effect of either size or book-to-market.

More recently, Viale et al. (2009) and Baek and Bilson (2014) explored common risk factors priced in stock returns of banks and other financial firms. Viale et al. (2009) focused on U.S. banks over the period 1986-2003 using the three-factor model of Fama and French (1993) and found no evidence suggesting that size or book-to-market are priced in bank stock returns (see Viale et al. (2009, p. 467)). Baek and Bilson (2014) also used the three-factor model of Fama and French (1993) and analysed U.S. financial firms between 1963-2012. Their results suggest a negative relation between size and average returns and a positive relation between book-to-market and average returns (see Baek and Bilson (2014, p. 18)). Baek and Bilson (2014) also analysed cross-sectional returns using one-way sort portfolios, and found evidence, similar to Barber and Lyon (1997), of both a size and a book-to-market premium (see Baek and Bilson (2014, p. 14)).

The banking literature briefly reviewed reveals conflicting findings about size and book-to-market. While evidence found by Barber and Lyon (1997) and Baek and Bilson (2014) suggests the existence of size and book-to-market premiums, the studies of Cooper et al. (2003) and Viale et al. (2009) found no effect.[2] Possible explanations for this discrepancy in results could relate to the methodologies used in the different studies and to the time periods explored. For the studies using one-way sort portfolios, Barber and Lyon (1997) and Baek and Bilson (2014) found significant book-to-market and size premiums. In contrast, Cooper et al. (2003) found no significant effect. This difference may possibly by explained by the different time periods analysed: Both Barber and Lyon (1997) and Baek and Bilson (2014) included earlier years compared to Cooper et al. (2003). Similarly, Baek and Bilson (2014) and Viale et al. (2009) both used the three-factor model of Fama and French (1993) to assess size and book-to-market anomalies and found different results. Again, differences relating to the time periods analysed may explain these discrepancies. Finally, only Cooper et al. (2003) used Fama and MacBeth (1973) cross-sectional regressions and found no significant effect for size and book-to-market. As for profitability and momentum, the predicting

[2]It may be worth mentioning that both Cooper et al. (2003) and Viale et al. (2009) looked specifically at banks, while Barber and Lyon (1997) and Baek and Bilson (2014) looked at nonfinancial firms in general, i.e. banks, insurance and real estate companies. Baek and Bilson (2014) used a fourth group, trading and investment companies. Both Barber and Lyon (1997) and Baek and Bilson (2014) further looked at the subset of banks and were able to confirm their main findings for this subset.

power of these two variables has, to the best of our knowledge, never been investigated in the banking industry.

Profitability and the cross-section of expected returns

Wang and Yu (2013) noted that most studies (e.g. Fama and French (2006, 2008), Novy-Marx (2013)) investigating the profitability premium are generally agnostic about whether this anomaly is due to rational or irrational pricing. For this reason, they do not discuss potential risk-related or behavioural explanations, and such explanations remain very scarce in the literature.[3]

Among the few authors that offer an explanation for the profitability premium, Sehgal (2012) proposed a risk-based explanation. He argued that investors might visualise profits as the reward for growth and innovation strategies. These strategies might bear higher operating or financial risk. For this reason, investors require higher returns. In other words, profit could be regarded as the reward for risk-bearing, therefore explaining why more profitable firms yield higher returns. Another possible line of argumentation is that more profitable firms are less risky than less profitable firms. Due to the higher earnings generated in past periods, more profitable firms have for example higher investment opportunities, while less profitable firms can be the subject of bankruptcy concerns. From this perspective, higher profitability should translate into lower returns. Results from the empirical literature, however, largely support a positive association between profitability and stock returns over a negative association.

Wang and Yu (2013) provided an explanation for the profitability premium based on irrational pricing. They argued that investors' behavioural bases such as underreaction to current profitability news generate an uninformed demand shock leading to high profitability firms being relatively underpriced compared to low profitability firms. Due to limits on arbitrage preventing rational investors from fully absorbing this shock, the price adjustment does not occur today, but only over a period of time, thus causing the profitability premium. Another possible explanation based on irrational pricing is that investors do not extrapolate enough future developments of profitability.

[3] Several of these studies, agnostic on the matter (e.g. Fama and French (2006), Novy-Marx (2013), and Fama and French (2014)), illustrate the underlying relationship between profitability and expected stock returns by using the dividend discount model.

Rather than reflecting a random walk, profitability in period t can be expected to be positively correlated with profitability in period $t-1$. Thus, profitability can be expected to be more or less constant over the short term, and maybe over the medium term as well. For example, a company's high profitability can be explained by its long-lived business philosophy, the implementation of a profitable strategy by its management, or from a particularly skilled labour force. Changes relating to these factors, and to other factors impacting on profitability, will inevitably happen over time. However, one can rationally expect that such changes will only happen gradually in most cases. Thus, one can expect that profitability will be more or less constant over time and should therefore be, on average, extrapolated over the short-term horizon.

Sehgal (2012) noted that, until recently, the profitability premium had become very little interest compared to other market anomalies. In the past few years, however, it has gained particular attention in the academic literature. Several empirical studies relating in a way or in another profitability to stock returns have been conducted (e.g. Fama and French (2006, 2008), Wang and Yu (2013), Novy-Marx (2013), Fama and French (2014), Hou et al. (in press), Ball, Gerakos, Linnainmaa, and Nikolaev (in press), Ball, Gerakos, Linnainmaa, and Nikolaev (2015)). Three of these studies (Fama and French (2006, 2008); Novy-Marx (2013)) are of particular interest for our study because they explore the relationship between profitability and the cross-section of monthly expected returns. These studies use a similar methodology, relying primarily on the Fama and MacBeth (1973) regression framework and on one-way sort portfolios to explore this thematic. They all excluded banks from the respective samples analysed.

In the first of these three studies, Fama and French (2006) analysed stock returns from U.S. firms between 1963-2003 in order to assess whether more profitable firms earn higher returns. They found that profitability had explanatory power in explaining subsequent average returns in Fama and MacBeth (1973) cross-sectional regressions. In the second study, Fama and French (2008) explored several market anomalies for U.S. firms between 1963-2005. In Fama and MacBeth (1973) cross-sectional regression, the authors found that profitability had a significant and positive effect on expected returns. However, results from one-way sorts of returns on profitability were largely inconclusive. These profitability sorts produced weak average long−short portfolio returns compared to the other anomalies analysed.

Finally, Novy-Marx (2013) analysed U.S. firms between 1963-2010 in a study focusing on the predicting power of profitability. Results from Fama and MacBeth (1973) monthly cross-sectional regression showed that profitability had roughly the same power as book-to-market in predicting average returns. In addition, results from one-way sorts of returns on profitability showed significantly positive long−short portfolio returns. Novy-Marx (2013) also showed the existence of significantly positive abnormal returns (significant intercepts) of the long−short portfolio (profitable minus unprofitable firms) relative to the Fama and French (1993) three-factor model. Thus, he concluded that the profitability premium found in the Fama and MacBeth (1973) regression was not captured by the various portfolios that proxy for risk. Novy-Marx (2013) attributed the clear-cut character of his findings, in contrast with the mixed results found by Fama and French (2008), to the different profitability proxies used. While Fama and French (2006, 2008) used income before extraordinary items divided by book equity, Novy-Marx (2013) employed gross profitability (revenues minus cost of goods sold) divided by total assets. He argued that gross profitability was a better proxy since it represents a firm's true economic profitability.

In addition, two recent studies explored the profitability premium using time series frameworks similar to the three-factor model of Fama and French (1993) or the four-factor model of Carhart (1997). Hou et al. (in press) used an empirical q-factor model consisting of the market factor, a size factor, an investment factor, and a profitability factor. They found that this model performed at least comparable to, and in several cases better than the three-factor model of Fama and French (1993) or the four-factor model of Carhart (1997). Similarly, Fama and French (2014), notably inspired by the results of Novy-Marx (2013), introduced a five-factor model that accounts for a profitability factor. They found that this model performed better than the three factor-model of Fama and French (1993).

Banking industry-specific variables

To our knowledge, only Cooper et al. (2003) have tried to relate banking industry-specific variables to the cross-section of stock market returns in an empirical framework. They analysed monthly returns of U.S. banks between 1986-1999 using one-way sorts of returns and Fama and MacBeth (1973) cross-sectional regression. They employed *"variables that have been shown to be important in determining the fundamental riskiness of banks or reflect recent changes in business practices that may affect bank risk"* to predict the cross-section of bank stock returns.[4] As previously noted, the authors investigated the relation between quarterly *changes* in several bank-level fundamental variables and stock market returns in order to analyse the effect of good/bad news shocks. Therefore, they analysed the stock market reaction to good/bad news shocks and did not try to predict the determinants of expected cross-sectional returns like we do in this study. Finally, they controlled for size and book-to-market value by including levels of these two variables. Results from one-way sorts and cross-sectional regressions showed that several variables relating to good/bad news shocks (changes in these variables) were significant. Relevant for this study, Cooper et al. (2003) did not find any significant effect for size or book-to-market (levels of these variables).

[4]The variables that Cooper et al. (2003) investigated are changes in earnings per share, loans-to-total assets, loan-loss reserves to total loans, non-interest income to net income, total unused loan commitments to total loans, total standby letters of credit to total loans, and interest rate swaps to total assets.

3.3. Proxy variables and methodology

3.3.1. Variables

In the empirical part, we explore whether lagged profitability and lags of industry-specific variables are good predictors of bank stock returns. In addition, we control for variables reflecting well-known market anomalies that are commonly used in cross-sectional asset pricing studies. In the following, we briefly discuss these variables, for which definitions are given in Table 3.1.

[Table 3.1 about here]

Profitability

As observed by Novy-Marx (2013), determining the best measure of economic profitability remains ultimately an empirical question. Fama and French (2006, 2008) used income before extraordinary items divided by book value of equity as proxy for profitability. Novy-Marx (2013) advocated that gross profit (revenues minus cost of goods sold) divided by total assets was a better proxy. He further argued that gross profits was the "cleanest" accounting measure of true economic profitability and added that "*the further down the income statement one goes, the more polluted profitability measures become, and the less related they are to true economic profitability*" (Novy-Marx, 2013, p. 2-3).

We take no ex ante position on the variable that best proxies profitability, but take note that different proxies have been used in past studies. Thus, we consider several potential proxies for profitability. Namely, we use Pre-impairment income scaled by total assets, Operating income scaled by total assets, Pre-tax income scaled by total assets, and Net income scaled by book equity. Worldscope income statement is displayed in Table 3.2 and our different proxies can be observed from this table. The different proxies considered relate to different positions of a bank's income statement. In addition, the analysis of correlation coefficients confirms that these variables are not identical and therefore measure different aspects of profitability.

[Table 3.2 about here]

We compute Pre-impairment income by adding Provision for loan losses to Operating income. Loan loss provisions are commonly used for earnings management purposes in banking. This practice is facilitated by the substantial latitude given to banks in determining the amount of provisions (see e.g. Bikker and Metzemakers (2005); Fonseca and Gonzalez (2008)). By subtracting loan loss provisions, earnings are drained from a potential source of manipulation of economic performance. Pre-impairment income can therefore be considered as a form of pre-managed profitability, making it arguably a good proxy of a bank's profitability. It is perhaps the variable that comes the closest to gross profitability, as defined by Novy-Marx (2013), in banking. However, absence manipulation, earnings are also drained from a real source of performance if loan losses provisions are not accounted for.

We further consider Operating income. Compared to Pre-impairment income, this measure may potentially be subject to earnings management through the manipulation of loan loss provisions. Absence manipulation, however, it can be considered as a more complete earnings proxy since it reflects income from a bank's core activities. The next variable considered is Pre-tax income. It is commonly seen as a measure of profitability giving a clear picture of the aspects that a bank can control. In addition, because Pre-tax income excludes taxes, this measure enables the profitability of companies to be compared across locations where corporate taxes differ. Finally, we consider Net income before extraordinary items. This variable, located at the bottom of the income statement, is commonly referred to as reported earnings and often used by practitioners and researchers as a proxy for profitability (e.g. Fama and French (2006, 2008)). All profitability proxies are expressed in % of total assets or book equity.

Banking industry-specific variables

As discussed earlier, cross-sectional asset pricing studies typically exclude financial institutions because they are different. Cooper et al. (2003) noted that, because of this different nature, there may exist important links between industry-specific variables and the cross-section of banks' stock returns. In the following, we discuss the industry-specific variables used in the empirical analysis.

Loan loss provisions (LLP/A)

Loan loss provisions are an indicator of the quality of a bank's loan portfolio. In principle, a higher ratio should suggest poor asset quality. It indicates that a bank can be expected to write off a substantial part of its loan portfolio in a foreseeable future, and is also likely to generate less interest income from these loans given the delicate financial situation of the debtors. Thus, the poor health of banks with higher ratios of loan loss provisions is likely to go in pair with poor stock returns. However, loan loss provisions are commonly used for earnings management purposes since banks have substantial latitude in determining these provisions. According to Beaver, Eger, Ryan, and Wolfson (1989), a higher ratio of loan loss provisions could even signal economic strength by indicating that investors perceive the earnings power of the bank as sufficiently strong to withstand a hit in earnings in the form of additional provisions. According to the same logic, a lower ratio may indicate that a bank is trying to avoid reporting losses (Ahmed et al., 1999). In this case, a higher ratio of loan loss provisions would suggest economic strength. It should therefore be associated with higher returns. We divide loan loss provisions by total assets (LLP/A) to reflect the share of total assets at risk.

Loan share (LS) and asset diversification (AD)

This study also aims to shed some light on the controversial issue of the value of non-traditional activities. In past decades, commercial banks have expanded their range of traditional activities (lending) into investment activities (e.g. fees, trading, insurance). In theory, one could expect that diversified banks that combine cash flows from non-correlated revenue sources should be more stable and profitable than their constituent parts (Baele et al., 2007; Cooper et al., 2003). Therefore, higher stock returns should go in pair with diversified banks. However, empirical research from DeYoung and Roland (2001) has shown that traditional activities are actually more stable and more recession-proof than investment activities. According to this view, less diversified banks focusing on traditional activities should earn higher returns.

To explore the impact of diversification on the cross-section of bank stock returns, we construct two variables inspired by Laeven and Levine (2007). The first variable, Loan share (LS), is constructed as the ratio of loans to total earnings assets, where total earnings assets include net loans and total investments (including securities).[5] High values (close to 100%) signal that a bank specialises mainly in commercial activities (lending), and low values (close to 0%) signal that a bank specialises in investment activities (non-lending).

The second variable, Asset diversification (AD) is constructed as

$$1 - \left| \frac{Net\ loans - Other\ earnings\ assets}{Total\ earnings\ assets} \right|, \tag{3.1}$$

where Other earnings assets is proxied by total investments. It reflects the degree of diversification of a bank, as opposed to its degree of specialisation. A bank focusing on commercial activities and a bank focusing on investment activities both have a value of zero since they are specialised institutions. A bank with a balanced mix of commercial and investment activities shows a value of one reflecting the high degree of diversification.[6]

Deposit share (DS)

As next variable, we use the ratio of customers' deposits to total liabilities. In the years leading to the global financial crisis, an increase in the share of wholesale, non-deposit, funding has been documented. It is commonly seen as one of the triggers of this crisis since it resulted in several U.S. and European banks being unable to renew this expiring short-term funding source (Claessens et al., 2012; International Monetary Fund, 2013; Laeven, 2011). It is indeed commonly argued that deposit funding is a relatively cheap and stable source of funding compared to market funding, presumably because deposits are usually covered by government guarantee (Beltratti & Stulz, 2012; Ivashina & Scharfstein, 2010; Laeven & Levine, 2007). A high deposit share (DS) may therefore be expected to be linked with higher stock returns.

Equity (BE/A)

Banks were initially excluded from cross-sectional stock return studies because of fundamental

[5] Laeven and Levine (2007) used data from Bankscope and defined total earning assets as the sum of loans, securities, and investments.

[6] Laeven and Levine (2007) also constructed two variables using income-based measures (interest versus noninterest income). Because of the substantial number of missing values for interest and noninterest income on Worldscope, including these alternative constructions would have resulted in a substantial number of observations being deleted, and we therefore did not construct these variables.

differences in leverage structure. Due to the intermediation function fulfilled by banks, high leverage is considered to be usual in the banking industry while it typically suggests financial distress in nonfinancial industries. Yet, extremely high leverage can also signal distress in the banking industry. Because equity represents a buffer against losses, a bank that holds more equity can be seen as more robust and less prone to solvability problems. However, equity is also seen as rather expensive and less profitable for its shareholders.

Traditional stock return determinants

In related studies, Novy-Marx (2013) and Fama and French (2006, 2008) used control variables accounting for well-known patterns in average stock returns in order to isolate the impact of profitability. We include the same variables as Novy-Marx (2013) and control for book-to-market (log(B/M)), size (log(ME)), and past performance measured at horizons of one month ($r_{0,1}$) and 12 to two months ($r_{2,12}$).[7] Previous research has shown that stocks with lower market capitalisation earn higher average returns (size anomaly) relative to stocks with higher market capitalisation. It has also shown that stocks with higher book-to-market ratio earn higher average returns (value anomaly) compared to stocks with lower book-to-market ratio. Finally, research has shown that stocks with high returns over the past year can be expected to have high returns in the next few months (momentum anomaly), while stocks with high returns over the past month can be expected to have low returns in the following month (short-term return reversal). There are therefore two distinct effects for past performance at different horizons.

Research from Jegadeesh (1990), Lehmann (1990) or Jegadeesh and Titman (1995) have documented that stocks tend to reverse from one month to the next (reversal rather than continuation). For example, Jegadeesh (1990) reported profits of about 2% per month over 1934-1987 using a reversal strategy that buys and sells stocks on the basis of their prior-month returns and holds them for one month. According to Avramov, Chordia, and Goyal (2006), however, the profitability of this strategy is questionable due to transaction costs likely to be expensive. Da, Liu, and Schaumburg (2014) noted that the existence of short-term reversal profits are typically attributed

[7] We follow recent studies (e.g. Cooper et al. (2003); Fama and French (2006, 2008); Gompers, Ishii, and Metrick (2003); Novy-Marx (2013), similar in terms of methodology and design, and do not include market beta in the Fama and MacBeth (1973) cross-sectional regressions.

to investors' overreaction to information (sentiment-based explanation) or derived from positions in small, high turnover, and illiquid stocks (liquidity-based explanation). According to the sentiment-based hypothesis, investors overreact to new information, causing an important price increase or decrease. In the following month, the overreaction is corrected, and this correction gives rise to the short-term return reversal. According the the liquidity-based explanation, high volume trading in one period causes prices to dramatically increase (or decrease). This effect is more likely among lower market capitalisations and illiquid stocks since one transaction can result more easily in high volume trading. The dramatic change in price is then corrected in the the next period as things get back to normal, and this would explain the short-term return reversal.

Recent evidence from Novy-Marx (2013) and Da et al. (2014) confirm the existence of short-term return reversal in recent time periods as well. Due to this short-term return reversal, empirical studies looking at the momentum anomaly, or using momentum as a control variable, often chose to either skip returns over the past month (e.g. Fama and French (2008, 2012)) or to include both past performance measured at horizons of one month and 12 to two months (e.g. Novy-Marx (2013) or this study).

3.3.2. Methodology

In order to assess the predicting power of the various explanatory variables on the cross-section of monthly returns, we use three main methods. First, we look at average monthly returns for portfolios formed on one-way sorts, and then at the results of Fama and MacBeth (1973) monthly cross-sectional regression. We further analyse intercepts from the four-factor model of Carhart (1997) to investigate the presence of excess returns above and beyond those suggested by the four-factor model. We also employ portfolios' Sharpe ratios to examine whether cross-sectional profitability is due to increased risk. We discuss these methods in more detail in the following.

Average monthly returns for portfolios formed on one-way sorts

As a first cut for relating the independent variables to the cross-section of expected bank stocks returns, we perform one-way quintile sorts. The main advantage of this approach is that it represents a simple picture of how average returns vary across the spectrum of a variable. Sorts of returns are, however, rather descriptive in nature as they do not allow to control for the impact of other variables (Fama & French, 2006).

Monthly returns are calculated from July through June of the following year. The portfolios are formed as follows. At the end of June of year t, stocks are allocated to quintiles based on lagged values of the independent variables. To ensure that values of the sort variables are known when the stocks are allocated to quintiles, we use accounting values from the fiscal period ending in year $t-1$ to form the quintile portfolios. For size, we take market capitalisation values from June of year t. For the two variables relating to past performance at different horizons, portfolios are updated monthly. Based on these quintile groupings, equally weighted (EW) returns are calculated.[8] In the following, we refer to the lower quintile portfolios as "short" (quintile 1) and to the higher as "long" (quintile 5).

In addition to showing average monthly returns of each quintile portfolio, we also show the returns obtained from long−short portfolios since the anomaly literature tends to emphasise long−short portfolio returns from positions in the extreme quintiles (Fama & French, 2008). We also compute two tests to assess the significance of the results. We use a t-test with the null hypothesis that the mean returns of long−short portfolios is zero. We also perform an analysis of variance (ANOVA) to test the null hypothesis of equality of mean returns across the quintile portfolios.

Fama and MacBeth (1973) monthly cross-sectional regression

Fama and MacBeth (1973) regression can correct for some of the shortcomings associated with one-way sorts of returns. In particular, multiple regression slopes can provide direct estimates of marginal effects and allow to draw inferences on the variables that have unique information about average returns and those that have little marginal ability to predict returns (Fama & French, 2006).[9]

Similar to Novy-Marx (2013), we include controls accounting for well-known anomalies such

[8] We use value-weighted portfolios for robustness purposes in Section 3.6.

[9] See Fama and French (2006) for a detailed comparison of one-way sorts of returns and Fama and MacBeth (1973) cross-sectional regressions.

as book-to-market (log(B/M)), size (log(ME)), and past performance measured at horizons of one month ($r_{0,1}$) and 12 to two months ($r_{2,12}$) in each specification. The regression setup is similar to that of the sorts. We estimate the regressions monthly, but again we update most of the explanatory variables annually at the end of June. Thus, we use accounting values from fiscal yearends between January and December of year $t-1$ to forecast monthly returns from July of t to June of $t+1$. Size (market capitalisation) is measured at the end of June of t. The two variables relating to past performance are again updated monthly. That is, to calculate $r_{2,12}$, values (total return index) of the oldest period is dropped in every new monthly regression (month 12 is dropped when it becomes month 13) and values from a newest period are added in every new monthly regression (month 1 is added when it becomes month 2). As for $r_{0,1}$, it is completely updated every month, taking the value that the dependent variable had in the previous month.

Time series regression of long−short portfolio profits on a four-factor model

The variables included in the four-factor model proxy for sensitivity to common risk factors in returns and have all been shown to significantly forecast future returns. This approach to testing asset pricing models was first introduced by Fama and French (1993). In the time series regression of portfolios of Fama and French (1993), monthly returns on portfolios are regressed on the returns to a market portfolio of stocks and on two portfolios mimicking size and book-to-market. The time series regression slopes are factors loadings that "*have a clear interpretation as risk-factor sensitivities*" (Fama & French, 1993, p. 4). This three-factor model was later extended by Carhart (1997) to a four-factor model including a portfolio mimicking momentum.

We use the four-factor model of Carhart (1997) and estimate the following time series regression:

$$R_t = \alpha + \beta_1 * MKT_t + \beta_2 * SMB_t + \beta_3 * HML_t + \beta_4 * UMD_t + \epsilon_t. \tag{3.2}$$

For each variable, the long−short portfolio R_t is regressed on the monthly return of the CRSP value-weighted index less the risk free rate (MKT), the monthly premium of the book-to-market factor (HML), the monthly premium of the size factor (SMB), and the monthly premium of winners minus losers (UMD).[10] The intercept α is the abnormal return on a strategy that buys quintile 5 portfolio and sells short quintile 1 portfolio. If quintile 5 differs significantly from quintile 1 in the characteristics of the mimicking portfolios (i.e. MKT, SMB, HML, UMD), differences in exposure to risk may explain the difference in returns (Gompers et al., 2003). If this is the case, these differences should be absorbed by the factors, and the intercept should be statistically insignificant. In contrast, a significant intercept would signal "excess returns" above and beyond that suggested by the four-factor model of Carhart (1997).[11]

In addition, finding evidence of a profitability premium not captured by the four-factor model would confirm the usefulness of integrating a profitability factor in a bank-specific asset-pricing model. Motivated by the results of Novy-Marx (2013) that found a significant intercept in the time-series portfolio regression framework, Fama and French (2014) developed a five-factor model integrating a profitability factor.

Portfolios' Sharpe ratio

As an alternative method to investigate whether the predictability found in cross-sectional regressions is due to increased risk, we examine Sharpe ratios for the average returns of the five quintile portfolios. This ratio is a measure of risk-adjusted performance. From a simple mean-variance standpoint, if the higher return portfolios are riskier, they should have a smaller Sharpe ratio coming from their higher standard deviations compared to portfolios with lower returns (Cooper et al., 2003). We follow Cooper et al. (2003) that used portfolio's Sharpe ratio for the same risk-adjustment purpose and compute the reported Sharpe ratios as average of monthly Sharpe ratios. These monthly Sharpe ratios are calculated as the monthly average in returns of a portfolio divided by its monthly standard deviation. In addition, we compute a t-test with the null hypothesis that the mean of monthly Sharpe ratios of long−short portfolios is zero.

[10] Data are obtained from Kenneth French's website. We are thankful for their provision.

[11] This technique was used by Gompers et al. (2003), Cooper et al. (2003), Novy-Marx (2013), or Von Lilienfeld-Toal and Ruenzi (2014), among others.

3.4. Data and descriptive statistics

3.4.1. Data

This study analyses monthly stock market returns of U.S. banks. Stock market data come from Datastream and accounting data from Worldscope. Due to data availability in the Worldscope database, the sample period covered in this study is from January 1980 to June 2014. Since we use lagged data up to 18 months in most specifications, the first monthly returns predicted are for July 1981. This time frame ensures the inclusion of periods with different business cycles and stock market conditions (e.g. Dot-com bubble, economic expansion of the early 2000s, financial crisis, Great Recession). Our sample is free from survivorship bias since we also consider banks that have been delisted during the sample period. We exclude banks with missing data on accounting or stock market variables.

Similar to Fama and French (2006, 2008), we address extreme values by winsorising all variables at the 1% and 99% levels.We also trim our data at the 1% and 99% levels in the robustness section, a technique used by Novy-Marx (2013). Although there is no absolute consensus in the way researchers deal with extreme values, trimming or winsorising are two widespread practices used in studies dealing with accounting and finance data. Extreme values are problematic since they can distort estimated coefficients, and thus need to be dealt with (Leone, Minutti-Meza, & Wasley, 2013).[12] To highlight the need to address extreme values, we display in Figure 3.1 box plots of the different variables used in order to show the dispersion of the data. As can be seen from the various plots, several variables appear to include extreme values that deviate substantially from the other observations.

[Figure 3.1 about here]

[12]Our choice of winsorising instead of trimming extreme values is mainly motivated by the fact that we consider trimming more "intrusive" than winsorising. By this we mean that winsorising has only an impact on one dimension of an observation. In contrast, trimming also impacts on all other dimensions since the observation is deleted from the sample. Thus, winsorising presents the advantage of preserving the number of observations in the sample and leaving unaffected the other dimensions of an observation. We opt for an across-the-board approach due to the number of observations in the sample that makes it fairly difficult to review potential outliers on an individual basis.

3.4.2. Descriptive statistics

Table 3.3 displays summary statistics for the variables used in Fama and MacBeth (1973) monthly cross-sectional regression. Our final sample includes 190,592 firm-months observations for each variable. Regressions are estimated monthly, but most of the explanatory variables are updated annually, i.e. the same value is used to predict 12 monthly returns. As can be seen, PII/A is bigger than OI/A since loan loss provisions, i.e. the difference between these two earnings measures, are almost always an expense. OI/A is in turn slightly bigger than PTI/A, indicating that the income stream occurring between these two positions is, on average, negative and represents an expense. Due to scaling effects, NI/E is substantially bigger than the other profitability proxies scaled by total assets. Expressed in absolute terms, however, pre-tax income is bigger than net income, reflecting the fact that tax expenses reduce income.

[Table 3.3 about here]

Average loan share is 71.05% while asset diversification is 55.18%. The first number reflects the fact that most banks in the sample are commercial banks, i.e. banks mainly active in loan-making (0 % indicates full specialisation in non-lending activities and 100% full specialisation in lending). The second number reflects the fact that the average bank is somewhat diversified (0% indicates full specialisation and 100% full diversification). These two findings complete each other since the fact that most banks concentrate their activities on loan-making also means that most banks are not fully diversified. Finally, customer deposits constitute the biggest part of banks' total liabilities (deposit share of 85.85%). This indicates that banks, on average, rely more heavily on traditional funding sources. Finally, the average equity ratio is 9.41%.

3.4.3. Correlation

Table 3.4 shows Spearman rank correlations between the independent variables employed in Fama and MacBeth (1973) regression. As expected, the various profitability proxies are strongly and significantly correlated to each other. They are, however, not identical. This confirms that the measures considered capture different aspects of profitability. Compared to the other correlations between profitability proxies, the correlation between PII/A and NI/E is substantially lower (0.67), which may in part be due to scaling effect. Finally, the correlation between PTI/A and OI/A is 0.97, indicating that these two variables are very close. There is also a significantly negative correlation between LLP/A and various profitability proxies (except PII/A). This indicates that a higher ratio of loan loss provisions is associated with lower profitability.

[Table 3.4 about here]

The significantly negative correlations between log(B/M) and the various profitability proxies (around 0.5) suggest that profitability is complementary to book-to-market. In addition, there is a significantly positive correlation, though slightly weaker, between log(ME) and various profitability proxies. As noted by Novy-Marx (2013) who found similar correlations among nonfinancial firms, this result reflects the fact that more profitable firms have higher market values. Profitable banks have, on average, lower book-to-market ratios and higher market capitalisations.

Log(ME) is significantly correlated with several industry-specific variables. The negative correlation between log(ME) and LS suggests that larger banks focus less on commercial activities and more on investment activities. Similarly, the positive correlation between log(ME) and AD suggests that larger banks are more diversified than smaller banks. Furthermore, the negative correlation between log(ME) and DS suggests that larger banks rely less heavily on customers' deposits compared to smaller banks. The negative correlation with BE/A indicates that larger banks tend to hold less equity.

Finally, LS and AD are practically perfectly (negatively) correlated (-0.97). While such a high coefficient may be surprising at first glance, this correlation reflects the fact that specialised institutions are predominantly banks with a higher loan share.[13] The remaining industry-specific variables do not have strong correlations with other variables.

[13] The highly significant correlation between LS and AD of -0.97 differs from the highly significant correlation between Type (assets) and Diversification (assets) of -0.48 found in the first paper of the thesis. This difference can be explained by differences relating to: the samples' composition (international vs. U.S. banks), the time periods analysed (1998-2013 vs. 1980-2014) and the type of correlation coefficients used (Pearson versus Spearman rank).

3.5. Results

3.5.1. Average monthly returns for portfolios formed on one-way sorts

Table 3.5 shows the average monthly returns for portfolios formed on one-way sorts of the lagged variables. Results suggest that a subset of the independent variables is important in predicting future stock returns.

[Table 3.5 about here]

Several long−short portfolios are statistically significant. For example, the results for log(B/M) means that banks with small book-to-market ratios (portfolio 1) earn significantly lower returns than banks with large book-to-market ratios (portfolio 5). Similarly, banks with large market capitalisation (log(ME)) earn significantly higher returns than banks with small market capitalisation (large firm premium), banks with large returns at a horizon of two to 12 ($r_{2,12}$) months earn higher monthly returns than banks with small returns at a horizon of two to 12 months (momentum), and banks with a large degree of diversification (AD) earn higher returns than banks with a small degree of diversification. Table 3.5 further shows that banks with large returns at a horizon of one month ($r_{0,1}$) earn significantly lower monthly returns than banks with small returns at a horizon of one month (short-term return reversal), while banks with large loan loss provisions (LLP/A) earn lower returns than banks with small loan loss provisions, and banks with large loan share (LS) earn lower returns than banks with small loan share.

In addition, one can observe statistically significant differences, as judged by the ANOVA test, in monthly returns across the portfolios formed from log(B/M), log(ME), $r_{0,1}$, and $r_{2,12}$. In the case of log(B/M), log(ME) and $r_{2,12}$, one can see an increasing pattern in average returns for most quintiles across the portfolio spectrum. For $r_{0,1}$, a decreasing pattern in returns can be observed. These results are in line with the results from the t-test of long−short portfolio returns.

For profitability, we find no significant returns from long−short portfolios. Similarly, we cannot reject the hypothesis of equality of monthly returns across the quintile portfolios. In addition, we do not observe any clear increasing or decreasing pattern in returns along the spectrum from small to large portfolio. While all mean returns from long−short portfolios are positive, reflecting the fact that average returns are higher in the portfolio of the most profitable firms compared to the portfolio of the least profitable firms, average returns are even higher in the portfolios in-between. Finally, we do not see any clear pattern in mean returns for DS and BE/A. One can, however, observe from the long−short portfolios that banks with a higher share of deposits (DS) and holding more equity (BE/A) tend to earn lower returns.

In terms of economic significance, $r_{0,1}$ produces the largest absolute long−short monthly returns. This means that, on average, stocks in the small portfolio (i.e. stocks with low returns in the previous month) earn returns that are larger by 2.078% compared to stocks in the large portfolio (i.e. stocks with high returns in the previous month) and reflects a short-term return reversal comparable in magnitude to the one reported by Jegadeesh (1990). Though smaller, long−short returns in the sorts on log(B/M), log(ME), $r_{2,12}$, LLP/A, LS and AD are also relatively large. For example for log(ME), they reflect the fact that stocks in the large portfolio earn average monthly returns larger by 0.603% relative to stocks in the small portfolio.

3.5.2. Fama and MacBeth (1973) monthly cross-sectional regression

Table 3.6 shows results of Fama and MacBeth (1973) monthly cross-sectional regression of returns on various profitability proxies and industry-specific variables. In each regression, we also control for well-known market anomalies. We start by discussing the results for these control variables.

[**Table 3.6 about here**]

The coefficient for log(B/M) is significantly positive across all specifications, reflecting the fact that banks with higher book-to-market ratios earn higher returns. This result underlines the existence of a book-to-market effect in the banking industry. Log(ME) is also significantly positive across all regressions, suggesting that larger banks earn higher returns compared to smaller banks. This result contrasts with the traditional view of a small firm effect (see e.g. Fama and French (2008) or Novy-Marx (2013)) found in the nonfinancial industry. The coefficient of $r_{0,1}$ is significantly negative across all specifications, which confirms the prediction of short-term return reversal. Compared to the other variables, the statistical significance of $r_{0,1}$ stands clearly out. Similar to Novy-Marx (2013), this variable has by far the highest t-value (not reported). As expected, $r_{2,12}$ is positive, indicating that stocks with high returns over the past year have high returns in the next few months. This variable has, however, the weakest statistical significance among the control variables.

Coefficients for all profitability proxies except PII/A are significantly positive at the 1% significance level. This result for PII/A means that our proxy for gross profitability in the banking industry fails to predict returns. The difference in magnitude between the coefficients of OI/A (or PTI/A) and NI/E of roughly 10% can be explained by scaling effects. As seen in the descriptive statistics, common equity is just under 10% of total assets. Thus, an increase in Net income representing 1% of total assets is roughly equivalent to an increase in Net income representing 10% of book equity. Overall, results suggest that banks with higher profitability earn higher subsequent returns compared to banks with lower profitability. In terms of significance, Net income (NI/E) has the largest predicting power among profitability proxies. Given the negative correlation found between the various profitability proxies and book-to-market, strategies formed on the basis of profitability can be a good hedge for strategies formed on book-to-market ratios.

Four industry-specific variables are statistically significant. The coefficient of loan loss provisions is significantly negative. This suggests that banks with higher ratios of loan loss provisions have lower returns compared to banks with lower ratios of loan loss provisions. This negative effect on cross-sectional returns may possibly reflect the poor quality of bank assets associated with higher LLP. The coefficient estimate associated with loan share is significantly negative, suggesting that commercial banks, i.e. banks focusing on lending, earn lower returns than investment banks focusing on other business lines. This supports the view that investment activities are perceived as more profitable by investors. The coefficient associated with asset diversification is significantly positive, suggesting that more diversified banks earn higher returns. As discussed earlier, the degree of diversification appears to be largely driven by the high proportion of commercial banks. Thus, the explanation for loan share may also apply to diversification. The coefficient estimate associated with DS is significantly positive. This suggests that banks with a higher share of deposits in total liabilities earn higher returns, thus supporting the hypothesis that a higher deposit share reflects greater access to cheap and stable funding and supports the view that deposits funding appears more profitable to investors. Finally, BE does not appear to play a major role.

3.5.3. Intercept from time series regression of long−short portfolio returns on a four-factor model

Results from time series regression of the long−short portfolios' returns on the four-factor model of Carhart (1997) are displayed in Table 3.7. With this framework, we examine whether differences in exposure to risk proxied by the four-factor model can explain the differences in returns. Significant intercepts signal excess returns above and beyond those suggested by the four-factor model.

[**Table 3.7 about here**]

Table 3.7 shows that log(B/M), $r_{0,1}$, LLP/A, LS and AD all have statistically significant intercepts at the highest confidence level. All these variables were already found to be significant in predicting the cross-section of bank stock returns, and we also found evidence of their predicting power in the one-way sort portfolios. Once again, past performance at a horizon of one month stands out from the other explanatory variables since the intercept of this variable suggests excess return of 2.12%. As for the profitability proxies, no intercept appears is highly significant. The economic explanation behind this is that the predictability found in the cross-section of monthly returns can be explained by the four-factor model. These results contrast with evidence from Novy-Marx (2013) of significant intercepts for the nonfinancial industry.

Taken together, one-way sort portfolios, Fama and MacBeth (1973) regression, and intercepts from time series regression provide reasonably strong evidence supporting the existence of bank-industry-wide cross-sectional predictability. This predictability comes from book-to-market, past performance at a horizon of one month, loan loss provisions, loan share, and asset diversification. The predicting power of past performance at a horizon of one month is particularly strong. In addition, elements of one-way sorts and/or Fama and MacBeth (1973) regressions also provide some evidence of predictability arising from various profitability proxies, size and deposit share. Particular attention should therefore be paid to these variables in the following sections focusing on risk-adjustment and robustness checks.

3.5.4. Portfolios' Sharpe ratios

We report results from portfolios' Sharpe ratios on Table 3.8. We saw earlier that the average returns from portfolios sorted e.g. on log(ME) or AD showed an increasing pattern across most quintiles. We can observe a similar pattern for Sharpe ratios. This tends to indicate that higher returns portfolios are not necessarily riskier than lower returns portfolios. Similarly, we found a decreasing pattern in returns for $r_{0,1}$ or LS. For these two variables, Table 3.8 shows the same decreasing pattern in Sharpe ratios. Overall, the pattern is of higher Sharpe ratios in the quintiles characterised by higher average returns, and lower Sharpe ratios in the quintiles characterised by lower average returns. From a mean-variance standpoint, this does not suggest that the higher performing portfolios are necessarily riskier. Thus, increased risk does not appear to be the main driver of the returns observed earlier.

[Table 3.8 about here]

3.6. Robustness tests

We conduct several robustness tests of our results. First, we repeat the cross-sectional regressions with a wider set of control variables. Second, we show the results of the cross-sectional regressions when we use trimming instead of winsorising to address extreme values. Third, we analyse whether our results are driven by the characteristics of small caps representing only a small fraction of total market equity. Fourth, we look at the evolution over time of the predicting power of the variables. Fifth, we use a three-factor model instead of a four-factor model to analyse whether the inclusion of a momentum factor can be responsible for the different results regarding excess returns of profitability between this study and the study of Novy-Marx (2013). Finally, we take a closer look at past performance at a horizon of one month since results for this variable stands out relative to the other variables.

Additional control variables

For robustness purposes, we repeat the cross-sectional regressions with a wider set of control variables consisting in all independent variables considered in the paper. We display the results in Table 3.9. Given the high correlation coefficients found earlier, we include only one profitability proxy per specification. Similarly, we do not include simultaneously LS and AD. With the exception of Operating income that loses its statistical significance, we come to similar results.

[**Table 3.9 about here**]

Alternative treatment of extreme values

In the paper, we used winsorising to address extreme values. For robustness purposes, we trim the variables at the 1% and 99% levels and show results of the cross-sectional regressions in Table 3.10. As can be seen, results do not substantially differ. The only exception is PII/A, which is now statistically significant.

[Table 3.10 about here]

Potential effect of small caps

As noted by Fama and French (2008), small caps can be influential in frameworks using equally weighted returns since each observation carries the same weight although small caps represents only a small fraction of the total market equity. In order to check whether our results are driven by characteristics of smaller market stocks, we take two measures. First, we use value-weighted returns instead of equally-weighted returns to compute average monthly returns for portfolios formed on one-way sorts. The results are displayed in Table 3.11.

[Table 3.11 about here]

Overall, results from VW returns indicate that small market capitalisations could be influential in our sample. For example, both LS and AD lose their statistical significance in the tests. In contrast, two profitability proxies (PII/A and NI/E) as well as DS and BE/A are now significant. For this reason, we exclude observations that belong to the small portfolio formed on market capitalisation and re-run the Fama and MacBeth (1973) monthly cross-sectional regressions. Results are displayed in Table 3.12. We also perform cross-sectional regressions including only observations that belong to the small portfolio and display the results in Table 3.13.

[Table 3.12 about here]

[Table 3.13 about here]

As can be seen, profitability loses its statistical significance when banks in the smaller portfolio sorted on market capitalisation are dropped from the sample. When only smaller market capitalisations are considered, however, profitability is again significant. Therefore, the significant results reported earlier for profitability are likely to be driven by characteristics of small banks, and do not appear to apply to the rest of the sample. Similarly, small market capitalisations appear to be influential in the results found for size. While log(ME) is significantly positive in the whole sample, it loses its significance when small market capitalisations are excluded. It is significantly positive again in the sample including only small market capitalisations. Finally, we use value-weighted returns to calculate the mean returns from long−short portfolios for time series regression and display the results in Table 3.14. Results reveal that only past performance at a horizon of one month has a significant intercept suggesting excess returns.

[Table 3.14 about here]

Evolution over time

Over our sample period from 1980 to 2014, the competitive nature and financial performance of the banking industry changed dramatically. For instance, the last half of this period was characterised by deregulation and increased competition resulting from the repealing of the Glass Steagall Act. As a consequence, we would expect a larger proportion of diversified banks in the second half of the sample. This may in turn result in a lesser effect of asset diversification.

We examine the stability of the cross-sectional regression results by splitting our sample into two equal subperiods. Results for the first subperiod (1981-1998) are displayed in Table 3.15 and results for the second subperiod (1999-2014) in Table 3.16. In the first subperiod, only NI/E, LLP/A, and AD are statistically significant. Among control variables, log(B/M) and $r_{0,1}$ are highly significant across all specifications, while log(ME) and $r_{2,12}$ are also significant in most specifications, but at a lower confidence level. As for the second subperiod, results are fairly close to those found in the sample that covers the whole time period.

[Table 3.15 about here]

[Table 3.16 about here]

One should, however, be careful while interpreting differences in results between the first and the second time period. A possible explanation for the different results is that predictors of expected returns have simply changed over time. Another possible explanation may lie in the structure of the data. Datastream and Bankscope provide data for substantially more banks in later years compared to earlier years. As a result, the second subperiod is characterised by substantially more observations (134,270) than the first subperiod (56,334).

We further investigate the evolution over time by showing monthly coefficient estimates from the first step of the Fama and MacBeth (1973) procedure in Figure 3.2. As can be seen, early years are characterised by important variations in the coefficient estimates of most profitability proxies, industry-specific variables, and past performance at a horizon of 12 to two months. This may be due to the lower number of observations available in these early years. In addition, the plots of several variables are characterised by larger variations in the monthly coefficient estimates in the years following the financial crisis. For past performance at a horizon of one month, however, the stability of monthly coefficient estimates is particularly striking, underlining once again the robustness of the short-term return reversal.

[**Figure 3.2 about here**]

Three- versus four-factor model

Novy-Marx (2013, p. 5, Table 2) found a significant intercept for profitability suggesting excess returns. Unlike this paper, he used the three-factor model of Fama and French (1993) and not the four-factor model of Carhart (1997), therefore not controlling for the effect captured by the portfolio mimicking momentum. We conduct time series regression of long−short portfolio on a three-factor model and report the results in Table 3.17. We find intercepts slightly more significant for the profitability proxies, thus suggesting that the momentum portfolio captures part of the difference in returns between banks in the most profitable portfolio and banks in the the least profitable portfolio. As can be seen from Table 3.2, the momentum factor was highly significant in almost all specifications, suggesting that it captures part of the difference in returns for most variables.

[Table 3.17 about here]

Short-term return reversal

This study has highlighted that the predicting power of past performance at a horizon of one month stands out from the predicting power of the other variables. In the one-way sort portfolios, we found a monthly return of 2.079% for the long−short portfolio that was substantially higher compared to the other variables. In Fama and MacBeth (1973) monthly cross-sectional regression, the significance of the coefficient estimate was also very high. In time series regression, we found a statistically significant intercept suggesting excess returns of 2.12%, which again was substantially higher compared to the other variables. Finally, we found short-term return reversal to be remarkably stable over time.

Given these results, we further investigate the robustness of short-term return reversal across the five portfolios sorted on size. It is sometimes argued that short-term return reversal is caused by one or a few high volume transactions among small and illiquid stocks. If the short-term return reversal observed in our study comes from the illiquid character of the small market capitalisations, the predicting power of past performance at a horizon of one month should be stronger among small market capitalisations (Avramov et al., 2006; Da et al., 2014). We use the setting of the first regression of Table 3.6, i.e. the one including PII/A and the four control variables. As can be seen from Table 3.18, the coefficient estimates of $r_{0,1}$ are highly significant in each quintile formed on market capitalisation and the coefficients do not vary substantially across quintiles. Thus, the strong predicting power of $r_{0,1}$ found in the paper does not appear to be driven by small, illiquid market capitalisations, but seems to apply to the whole sample.

[Table 3.18 about here]

3.7. Conclusion

This study investigates the predicting power of profitability, industry-specific, and traditional anomaly variables on the cross-section of bank stock returns. Banks are typically excluded from cross-sectional asset pricing studies because they are different from nonfinancial firms. As a result, the existence of market anomalies, notably the profitability premium that has attracted particular attention in recent years, remains unclear for a large number of listed companies. In addition, important links between industry-specific variables and expected stock returns may be a direct consequence of the different nature of banks.

Findings about the profitability premium are mixed. Evidence from Fama and MacBeth (1973) cross-sectional regression suggests a positive relationship between profitability and expected stock returns. However, further analysis shows that small market capitalisations are very influential in explaining this result; once the smallest market capitalisations are excluded from the analysis, the statistical significance of the relationship disappears. In addition, results from one-way sorts of returns on profitability are largely inconclusive and do not point to the existence of a profitability premium. Similarly, evidence indicating the presence of abnormal returns suggested by significant intercepts of long−short portfolios regressed on the four-factor model of Carhart (1997) are very limited. These findings contrast with recent, clear-cut evidence from Novy-Marx (2013) suggesting that profitability is a strong predictor of expected cross-sectional returns. Thus, the profitability premium seems to be much more pronounced among nonfinancial firms than it is in the banking industry.

Evidence further shows that, among market anomalies, book-to-market and past performance at a horizon of one month are strong predictors of the cross-section of expected returns. Regarding industry-specific variables, we find that loan loss provisions, loan share, and activity diversification can all predict expected bank stock returns. For all these variables, we find convincing evidence both in the one-way sort portfolios, Fama and MacBeth (1973) cross-sectional regression, as well as significant abnormal returns relative to the four-factor model of Carhart (1997). Results relating to past performance at a horizon of one month (short-term return reversal) are particularly strong both in terms of statistical and economic significance. In the one-way sort portfolios, we find a monthly returns of 2.079% for the long−short portfolio as well as a statistically significant intercept suggesting excess returns of 2.12% in time series regression.

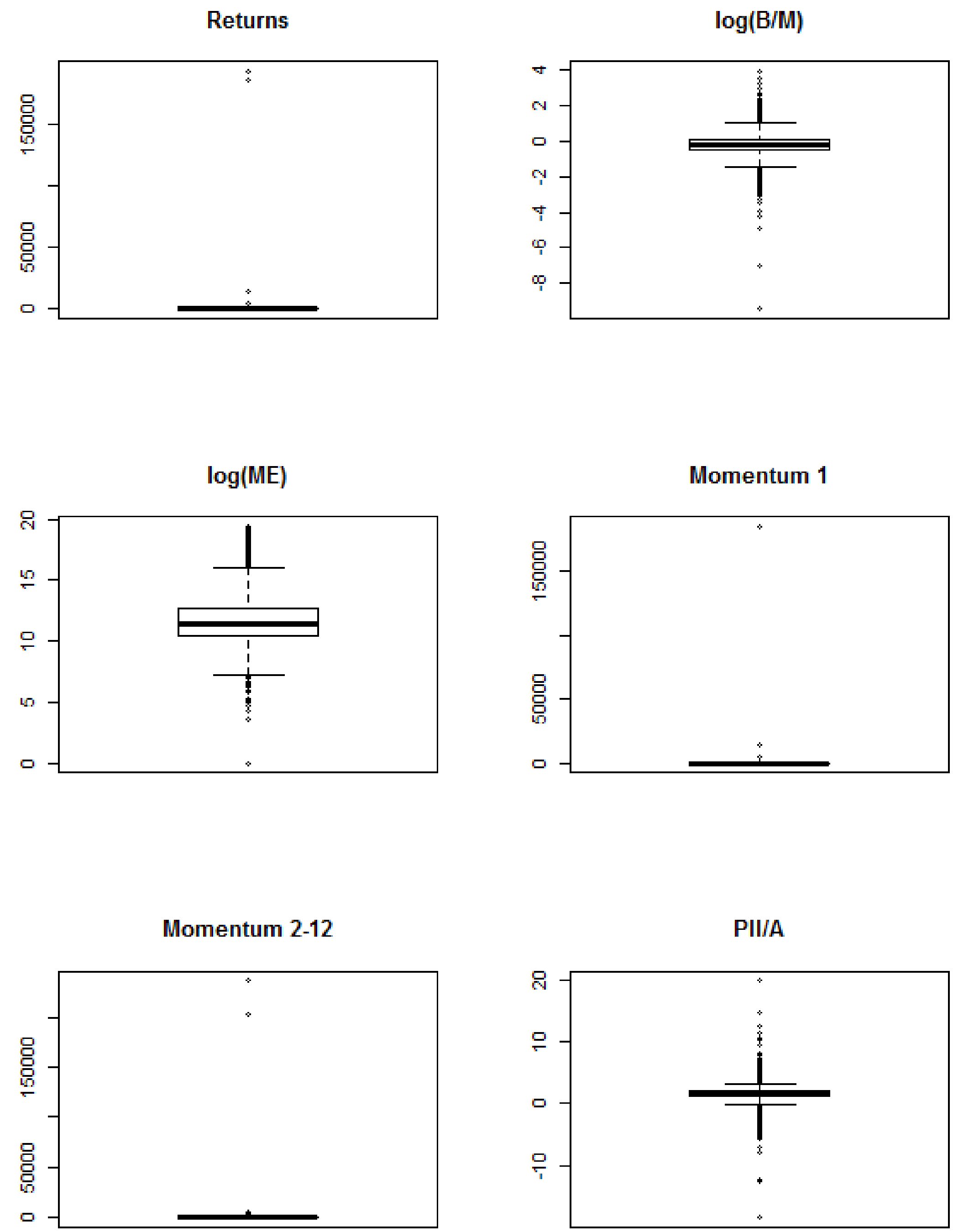
Table 3.1: Variables description

Variable	Description and source
Outcome variable	
Returns	Monthly stock market returns constructed from the total return index of Thomson Reuters Datastream (in %). Datastream
Profitability variables	
PII/A	Pre-impairment income, representing operating income before provision for loan losses, divided by total assets (in %). Worldscope
OI/A	Operating income, representing the difference between sales and total operating expenses, divided by total assets (in %). Worldscope
PTI/A	Pre-tax income, representing all income/loss before any federal, state or local taxes (extraordinary items reported net of taxes are excluded), divided by total assets (in %). Worldscope
NI/E	Net income before extraordinary items/preferred dividends, representing income before extraordinary items and preferred and common dividends, but after operating and non-operating income and expense, reserves, income taxes, minority interest and equity in earnings, divided by book equity (in %). Datastream
Bank-industry specific variables	
LLP/A	Loan loss provisions, representing losses that the bank expects to take as a result of uncollectable or troubled loans, divided by total assets (in %). Worldscope
LS	Loan share, defined as net loans divided by the sum of net loans plus total investments in securities (in %). Worldscope
AD	Asset diversification, defined as one minus the absolute value of the difference between net loans and total investments in securities divided by the sum of net loans plus total investments in securities (in %). Worldscope
DS	Deposits share, defined as the share of customers' deposits divided by total liabilities (in %). Worldscope
BE/A	Book equity, representing common shareholders' investment in a company, divided by total assets (in %). Worldscope
Traditional stock returns determinants	
log(B/M)	Logarithm of book equity to market equity, representing the balance sheet value of the ordinary (common) equity divided by the market value of ordinary (common) equity. Datastream
log(ME)	Logarithm of market capitalisation. Datastream
$r_{1,0}$	Past returns at horizon of one month (in %). Datastream
$r_{12,2}$	Past returns at horizon of 12 to two months (in %). Datastream

Table 3.2: Worldscope income statement

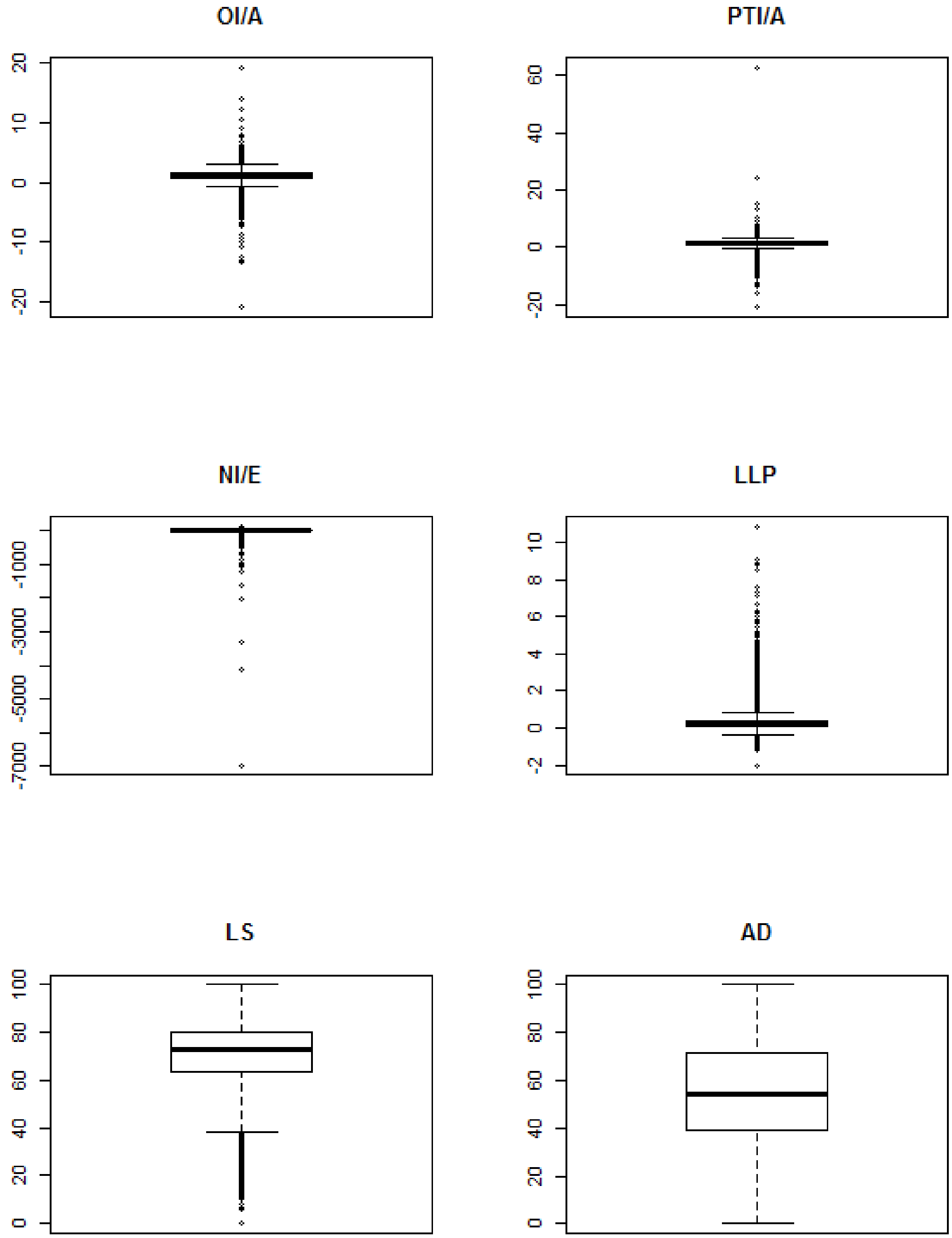
- 01016 Interest Income - Total
  - 01007 Interest and Fees on Loans
  - 01008 Interest Income on Federal Funds
  - 01009 Interest Income on Bank Deposits
  - 01010 Interest Income on Government Securities
  - 01011 Other Interest or Dividend Income
- 01075 Interest Expense - Total
  - 01072 Interest Expense on Bank Deposits
  - 01073 Interest Expense on Federal Funds
  - 01074 Interest Expense on Other Borrowed Funds
  - 01251 Interest Expense on Debt
  - 01255 Interest Capitalized
- 01076 Net Interest Income
- 01021 Non-Interest Income
  - 01018 Foreign Exchange Income
  - 01270 Gains/Losses on Sale of Securities - Pre-tax
  - 01266 Non-Operating Interest Income
  - 01017 Trading Account Income
  - 01019 Trusts & Fiduciary Income/Commission & Fees
    - 01014 Trust Income
    - 01015 Commission & Fees
  - 01020 Other Operating Income
- 01245 Non-Interest Expense
  - 01084 Staff Costs
  - 01085 Equipment Expense
  - 04049 Depreciation and Depletion
  - 01204 Taxes Other than Income Taxes
  - 01302 Operating Provisions
  - 01230 Other Operating Expenses
- **01271 Provision for Loan Losses**
- **01250 Operating Income**
- 01253 Extraordinary Credit - Pre-tax
- 01254 Extraordinary Charge - Pre-tax
- 01262 Other Income/Expense - Net
- 01267 Pre-tax Equity in Earnings
- 01301 Reserves - Increase/Decrease
- **01401 Pre-tax Income**
- 01451 Income Taxes
  - 18186 Current Domestic Income Tax
  - 18187 Current Foreign Income Tax
  - 18188 Deferred Domestic Income Tax
  - 18189 Deferred Foreign Income Tax
  - 18185 Income Tax Credits
- 01501 Minority Interest
- 01503 Equity in Earnings
- 01504 After Tax Other Income/Expense
- 01505 Discontinued Operations
- **01551 Net Income before Extraordinary Items/Preferred Dividends**
- 01701 Preferred Dividend Requirements
- 01706 Net Income after Preferred Dividends (Basic EPS)
- 01601 Extraordinary Items & Gain/Loss Sale of Assets

Figure 3.1: Box plots to screen the presence of extreme values



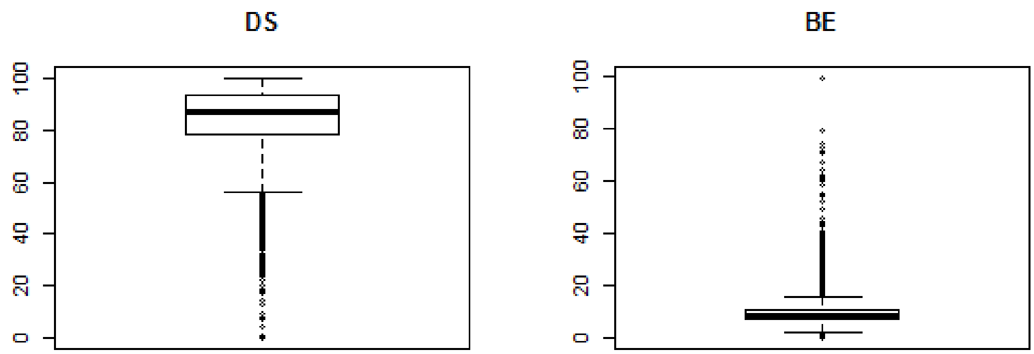
The figures show the variation in the raw, unwinsorised/untrimmed sample of data used in Fama and MacBeth (1973) monthly cross-sectional regression by means of box plots.

Figure 3.1: Box plots to screen the presence of extreme values (continued)



The figures show the variation in the raw, unwinsorised/untrimmed sample of data used in Fama and MacBeth (1973) monthly cross-sectional regression by means of box plots.

Figure 3.1: Box plots to screen the presence of extreme values (continued)



The figures show the variation in the raw, unwinsorised/untrimmed sample of data used in Fama and MacBeth (1973) monthly cross-sectional regression by means of box plots.

Table 3.3: Summary statistics

	Obs.	Mean	S.D.	Min.	Q25	Median	Q75	Max.
Returns	190,604	0.908	9.009	−29.272	−3.241	0.490	4.910	33.330
PII/A	190,604	1.495	0.751	−1.950	1.103	1.516	1.930	3.452
OI/A	190,604	1.120	1.015	−4.449	0.772	1.254	1.684	3.342
PTI/A	190,604	1.065	1.105	−5.054	0.741	1.230	1.666	3.178
NI/E	190,604	7.707	12.674	−81.657	5.490	9.981	13.531	27.056
log(B/M)	190,604	−0.196	0.511	−1.421	−0.531	−0.231	0.105	1.470
log(ME)	190,604	11.683	1.749	7.904	10.480	11.432	12.687	16.738
$r_{0,1}$	190,604	0.910	8.988	−29.272	−3.249	0.490	4.910	33.332
$r_{2,12}$	190,604	10.222	31.021	−79.396	−7.840	8.447	27.343	111.187
LLP/A	190,604	0.370	0.531	−0.089	0.096	0.205	0.401	3.390
LS	190,604	71.049	13.218	26.529	63.689	72.499	80.368	94.784
AD	190,604	55.181	21.805	9.659	39.026	54.538	71.152	98.871
DS	190,604	84.853	11.396	42.643	78.602	87.190	93.642	100.000
BE/A	190,604	9.410	4.117	1.946	7.065	8.660	10.551	35.518

The table provides summary statistics for the variables used in Fama and MacBeth (1973) monthly cross-sectional regression. The sample covers U.S. banks between 1980-2014. All variables are winsorised at the 1% and 99% levels. Regressions are estimated monthly, but most of the explanatory variables are updated annually, i.e. the same value is used to predict 12 monthly returns. $r_{0,1}$ and $r_{2,12}$ are updated monthly. Returns are monthly returns of the total return index of Datastream, PII/A is Pre-impairment operating income divided by total assets, OI/A is Operating income divided by total assets, PTI/A is Pre-tax income divided by total assets, NI/E is Net income divided by book value of equity, log(B/M) is the natural logarithm of book-to-market, log(ME) is the natural logarithm of market equity, $r_{0,1}$ is past performance measured at a horizon of one month, $r_{2,12}$ is past performance measured at a horizon of 12 to two months, LLP/A is loan loss provisions divided by total assets, LS is loan share, AD is asset diversification, DS is deposit share, BE/A is book equity divided by total assets. All variables except log(B/M) and log(ME) are expressed in %.

Table 3.4: Spearman rank correlations between independent variables used in Fama and MacBeth (1973) monthly cross-sectional regression

	PII/A	OI/A	PTI/A	NI/E	B/M	ME	$r_{0,1}$	$r_{2,12}$	LLP/A	LS	AD	DS
OI/A	0.89											
	(0.00)											
PTI/A	0.86	0.97										
	(0.00)	(0.00)										
NI/E	0.67	0.73	0.77									
	(0.00)	(0.00)	(0.00)									
log(B/M)	−0.48	−0.55	−0.54	−0.53								
	(0.00)	(0.00)	(0.00)	(0.00)								
log(ME)	0.45	0.38	0.37	0.46	−0.39							
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)							
$r_{0,1}$	0.02	0.02	0.02	0.03	0.05	0.05						
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)						
$r_{2,12}$	0.07	0.08	0.08	0.12	0.17	0.15	0.06					
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)					
LLP/A	0.03	−0.33	−0.33	−0.17	0.20	0.06	0.00	−0.02				
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.75)	(0.00)				
LS	0.04	−0.03	−0.03	−0.09	0.03	−0.13	−0.04	−0.10	0.18			
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)			
AD	−0.03	0.03	0.03	0.10	−0.03	0.13	0.04	0.11	−0.15	−0.97		
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		
DS	0.05	0.04	0.05	−0.07	0.04	−0.29	0.01	0.04	0.05	0.03	−0.01	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	
BE/A	0.17	0.24	0.23	−0.26	0.00	−0.11	−0.01	−0.05	−0.26	0.02	−0.02	0.20
	(0.00)	(0.00)	(0.00)	(0.00)	(0.92)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

The table provides Spearman rank correlations between independent variables used in Fama and MacBeth (1973) monthly cross-sectional regression. The sample covers U.S. banks between 1980-2014. All variables are winsorised at the 1% and 99% levels. Returns are monthly returns of the total return index of Datastream, PII/A is Pre-impairment operating income divided by total assets, OI/A is Operating income divided by total assets, PTI/A is Pre-tax income divided by total assets, NI/E is Net income divided by book value of equity, log(B/M) is the natural logarithm of book-to-market, log(ME) is the natural logarithm of market equity, $r_{0,1}$ is past performance measured at a horizon of one month, $r_{2,12}$ is past performance measured at a horizon of 12 to two months, LLP/A is loan loss provisions divided by total assets, LS is loan share, AD is asset diversification, DS is deposit share, BE/A is book equity divided by total assets.

Table 3.5: Average monthly returns for portfolios formed on one-way sorts

	(1)	(2)	(3)	(4)	(5)	(5)−(1)[a]	ANOVA[b]
PII/A	0.647	0.879	0.870	0.812	0.674	0.027	0.985
OI/A	0.566	0.926	0.873	0.787	0.733	0.167	0.772
PTI/A	0.537	0.934	0.861	0.833	0.720	0.183	0.695
NI/E	0.516	0.912	0.856	0.836	0.763	0.247	0.537
log(B/M)	0.521	0.655	0.858	0.905	0.962	0.440***	0.093*
log(ME)	0.361	0.791	0.809	0.962	0.963	0.602**	0.056*
$r_{0,1}$	1.635	1.141	0.950	0.585	−0.443	−2.079***	0.000***
$r_{2,12}$	0.294	0.862	0.925	0.940	0.869	0.575***	0.071*
LLP/A	0.876	0.865	0.772	0.887	0.481	−0.395**	0.254
LS	0.890	0.858	0.898	0.746	0.493	−0.396***	0.175
AD	0.464	0.763	0.878	0.853	0.929	0.465***	0.125
DS	0.819	0.750	0.766	0.787	0.761	−0.058	0.906
BE/A	0.704	0.787	0.901	0.815	0.677	−0.027	0.968

The table shows averages of monthly equal-weight stock returns for each portfolio and for the (5)−(1) portfolio obtained from long-short positions in the extreme quantiles. The sample covers U.S. banks between 1980-2014. All variables are winsorised at the 1% and 99% levels. Average monthly returns are expressed in %; Returns are monthly returns of the total return index of Datastream, PII/A is Pre-impairment operating income divided by total assets, OI/A is Operating income divided by total assets, PTI/A is Pre-tax income divided by total assets, NI/E is Net income divided by book value of equity, log(B/M) is the natural logarithm of book-to-market, log(ME) is the natural logarithm of market equity, $r_{0,1}$ is past performance measured at a horizon of one month, $r_{2,12}$ is past performance measured at a horizon of 12 to two months, LLP/A is loan loss provisions divided by total assets, LS is loan share, AD is asset diversification, DS is deposit share, BE/A is book equity divided by total assets. [a] t-test and significance; The null hypothesis is that the mean of long−short portfolios is zero. [b] p-values for the ANOVA test; The null hypothesis is equality of average monthly portfolio returns across quantile sorts for a given sort. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 3.6: Fama and MacBeth (1973) monthly cross-sectional regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PII/A	0.035								
	(0.603)								
OI/A		0.168^{***}							
		(0.008)							
PTI/A			0.179^{***}						
			(0.006)						
NI/E				0.022^{***}					
				(0.000)					
LLP/A					-0.752^{***}				
					(0.000)				
LS						-0.007^{**}			
						(0.020)			
AD							0.006^{***}		
							(0.001)		
DS								0.010^{***}	
								(0.006)	
BE/A									-0.007
									(0.672)
log(B/M)	0.734^{***}	0.828^{***}	0.837^{***}	0.853^{***}	0.815^{***}	0.739^{***}	0.752^{***}	0.806^{***}	0.749^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(ME)	0.183^{***}	0.182^{***}	0.183^{***}	0.174^{***}	0.213^{***}	0.191^{***}	0.192^{***}	0.224^{***}	0.184^{***}
	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
$r_{0,1}$	-0.107^{***}	-0.108^{***}	-0.108^{***}	-0.109^{***}	-0.108^{***}	-0.107^{***}	-0.108^{***}	-0.107^{***}	-0.107^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$r_{2,12}$	0.005^{*}	0.004	0.004	0.003	0.003	0.004	0.004	0.005^{*}	0.005^{*}
	(0.055)	(0.103)	(0.107)	(0.191)	(0.267)	(0.100)	(0.101)	(0.082)	(0.078)
Avg. R^2	0.10	0.10	0.10	0.11	0.10	0.10	0.10	0.10	0.10
Obs.	190,604	190,604	190,604	190,604	190,604	190,604	190,604	190,604	190,604
Months	396	396	396	396	396	396	396	396	396

The table shows average slopes from monthly cross-section regressions to predict stock returns of U.S. banks between 1980 and 2014. All variables are winsorised at the 1% and 99% levels. Returns are monthly returns of the total return index, PII/A is Pre-impairment operating income divided by total assets, OI/A is Operating income divided by total assets, PTI/A is Pre-tax income divided by total assets, NI/E is Net income divided by book value of equity, LLP/A is loan loss provisions divided by total assets, LS is loan share, AD is asset diversification, DS is deposit share, BE/A is book equity divided by total assets, log(B/M) is the natural logarithm of book-to-market, log(ME) is the natural logarithm of market equity, $r_{0,1}$ is past performance measured at a horizon of one month, $r_{2,12}$ is past performance measured at a horizon of 12 to two months. p-values under parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 3.7: Time series regression of long−short portfolios' returns on the four-factor model of Carhart (1997)

Ranked by	α	β_{MKT}	β_{SMB}	β_{HML}	β_{UMD}	R^2	Months
PII/A	−0.04 (0.78)	0.08 (0.03)**	−0.10 (0.06)*	0.08 (0.16)	0.00 (0.93)	0.03	396
OI/A	0.25 (0.14)	−0.07 (0.06)*	−0.18 (0.00)***	−0.09 (0.15)	0.03 (0.49)	0.04	396
PTI/A	0.28 (0.10)*	−0.09 (0.02)**	−0.18 (0.00)***	−0.11 (0.07)*	0.03 (0.43)	0.05	396
NI/E	0.25 (0.14)	0.04 (0.31)	−0.26 (0.00)***	−0.07 (0.24)	0.03 (0.40)	0.05	396
log(B/M)	0.39 (0.01)**	−0.02 (0.52)	0.15 (0.01)***	0.09 (0.12)	0.03 (0.46)	0.02	396
log(ME)	0.21 (0.39)	0.48 (0.00)***	−0.20 (0.01)**	0.28 (0.00)***	0.02 (0.73)	0.17	396
$r_{0,1}$	−2.12 (0.00)***	−0.08 (0.04)**	−0.10 (0.10)*	0.05 (0.44)	0.14 (0.00)***	0.07	396
$r_{2,12}$	0.48 (0.00)***	−0.04 (0.27)	−0.15 (0.01)***	−0.08 (0.19)	0.27 (0.00)***	0.16	396
LLP/A	−0.58 (0.00)***	0.23 (0.00)***	0.13 (0.01)**	0.25 (0.00)***	−0.10 (0.00)***	0.18	396
LS	−0.54 (0.00)***	0.15 (0.00)***	0.04 (0.34)	0.14 (0.00)***	0.00 (0.98)	0.07	396
AD	0.61 (0.00)***	−0.14 (0.00)***	−0.04 (0.38)	−0.13 (0.01)***	0.00 (0.92)	0.07	396
DS	0.23 (0.07)*	−0.35 (0.00)***	0.05 (0.23)	−0.21 (0.00)***	0.01 (0.71)	0.28	396
BE/A	0.23 (0.10)	−0.31 (0.00)***	0.02 (0.73)	−0.19 (0.00)***	0.00 (0.95)	0.20	396

The table provides results from time series regression of average equal-weight returns from long−short portfolios for U.S. banks between 1980-2014 on a four-factor model. α represents the excess returns, i.e. returns above and beyond that suggested by the four-factor model of Carhart (1997). Returns are monthly returns of the total return index, PII/A is Pre-impairment operating income divided by total assets, OI/A is Operating income divided by total assets, PTI/A is Pre-tax income divided by total assets, NI/E is Net income divided by book value of equity, log(B/M) is the natural logarithm of book-to-market, log(ME) is the natural logarithm of market equity, $r_{0,1}$ is past performance measured at horizon of one month, $r_{2,12}$ is past performance measured at horizon of 12 to two months, LLP/A is loan loss provisions divided by total assets, LS is loan share, AD is asset diversification, DS is deposit share, BE/A is book equity divided by total assets. p-values under parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 3.8: Portfolios' Sharpe ratios

	(1)	(2)	(3)	(4)	(5)	(5)−(1)[a]
PII/A	0.049	0.116	0.118	0.125	0.103	0.054***
OI/A	0.041	0.122	0.120	0.126	0.112	0.071***
PTI/A	0.038	0.125	0.122	0.130	0.113	0.074***
NI/E	0.040	0.123	0.120	0.128	0.105	0.065***
log(B/M)	0.055	0.090	0.112	0.121	0.105	0.050***
log(ME)	0.035	0.104	0.109	0.133	0.136	0.101**
$r_{0,1}$	0.182	0.157	0.129	0.083	−0.064	−0.247***
$r_{2,12}$	0.027	0.123	0.138	0.139	0.098	0.070***
LLP/A	0.101	0.133	0.107	0.122	0.039	−0.062***
LS	0.119	0.107	0.122	0.095	0.045	−0.074***
AD	0.041	0.095	0.120	0.109	0.125	0.084***
DS	0.101	0.094	0.088	0.098	0.098	−0.003
BE/A	0.059	0.095	0.120	0.115	0.098	0.039**

The table provides Sharpe ratios of the one-way sort portfolios for U.S. banks between 1980-2014 using equal-weight returns. The Sharpe ratios are computed as average of monthly Sharpe ratios. Returns are monthly return of the total return index, PII/A is Pre-impairment operating income divided by total assets, OI/A is Operating income divided by total assets, PTI/A is Pre-tax income divided by total assets, NI/E is Net income divided by book value of equity, log(B/M) is the natural logarithm of book-to-market, log(ME) is the natural logarithm of market equity, $r_{0,1}$ is past performance measured at horizon of one month, $r_{2,12}$ is past performance measured at horizon of 12 to two months, LLP/A is loan loss provisions divided by total assets, LS is loan share, AD is asset diversification, DS is deposit share, BE/A is book equity divided by total assets. [a] t-test and significance; The null hypothesis is that the mean Sharpe ratio of long−short portfolios is zero.

Table 3.9: Fama and MacBeth (1973) monthly cross-sectional regression with additional control variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PII/A	0.087				0.097			
	(0.191)				(0.143)			
OI/A		0.084				0.093		
		(0.198)				(0.151)		
PTI/A			0.154**				0.162**	
			(0.018)				(0.013)	
NI/E				0.015**				0.015**
				(0.014)				(0.012)
LLP/A	−0.619***	−0.539***	−0.468***	−0.439***	−0.610***	−0.520***	−0.450***	−0.421***
	(0.000)	(0.001)	(0.003)	(0.005)	(0.000)	(0.001)	(0.004)	(0.006)
LS	−0.009***	−0.009***	−0.009***	−0.010***				
	(0.003)	(0.003)	(0.002)	(0.001)				
AD					0.007***	0.007***	0.007***	0.007***
					(0.000)	(0.000)	(0.000)	(0.000)
DS	0.014***	0.014***	0.014***	0.015***	0.013***	0.013***	0.013***	0.014***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BE/A	−0.020	−0.020	−0.027*	−0.016	−0.018	−0.018	−0.025*	−0.013
	(0.182)	(0.185)	(0.066)	(0.287)	(0.234)	(0.238)	(0.094)	(0.382)
log(B/M)	0.920***	0.920***	0.945***	0.954***	0.932***	0.931***	0.955***	0.960***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(ME)	0.226***	0.226***	0.223***	0.229***	0.226***	0.226***	0.223***	0.229***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$r_{0,1}$	−0.113***	−0.113***	−0.113***	−0.113***	−0.114***	−0.114***	−0.114***	−0.114***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$r_{2,12}$	0.001	0.001	0.000	0.000	0.001	0.001	0.000	0.000
	(0.799)	(0.800)	(0.865)	(0.934)	(0.820)	(0.819)	(0.885)	(0.917)
Avg. R^2	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13
Obs.	190,604	190,604	190,604	190,604	190,604	190,604	190,604	190,604
Months	396	396	396	396	396	396	396	396

The table shows average slopes from monthly cross-section regressions to predict stock returns of U.S. banks between 1980 and 2014. All variables are winsorised at the 1% and 99% levels. Returns are monthly returns of the total return index, PII/A is Pre-impairment operating income divided by total assets, OI/A is Operating income divided by total assets, PTI/A is Pre-tax income divided by total assets, NI/E is Net income divided by book value of equity, LLP/A is loan loss provisions divided by total assets, LS is loan share, AD is asset diversification, DS is deposit share, BE/A is book equity divided by total assets, log(B/M) is the natural logarithm of book-to-market, log(ME) is the natural logarithm of market equity, $r_{0,1}$ is past performance measured at a horizon of one month, $r_{2,12}$ is past performance measured at a horizon of 12 to two months. p-values under parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 3.10: Fama and MacBeth (1973) monthly cross-sectional regression - Sample with all variables trimmed

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PII/A	0.196***								
	(0.004)								
OI/A		0.281***							
		(0.000)							
PTI/A			0.285***						
			(0.000)						
NI/E				0.035***					
				(0.000)					
LLP/A					−0.517***				
					(0.000)				
LS						−0.012***			
						(0.000)			
AD							0.008***		
							(0.000)		
DS								0.010***	
								(0.003)	
BE/A									0.010
									(0.484)
log(B/M)	0.846***	0.930***	0.942***	1.001***	0.847***	0.803***	0.808***	0.849***	0.810***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(ME)	0.161***	0.161***	0.164***	0.144**	0.185***	0.174***	0.177***	0.200***	0.174***
	(0.005)	(0.005)	(0.004)	(0.011)	(0.001)	(0.002)	(0.002)	(0.000)	(0.002)
$r_{0,1}$	−0.110***	−0.111***	−0.112***	−0.111***	−0.112***	−0.111***	−0.112***	−0.111***	−0.111***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$r_{2,12}$	0.003	0.002	0.002	0.001	0.001	0.002	0.002	0.002	0.002
	(0.232)	(0.448)	(0.450)	(0.541)	(0.642)	(0.400)	(0.445)	(0.308)	(0.397)
Avg. R^2	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
Obs.	166,439	166,439	166,439	166,439	166,439	166,439	166,439	166,439	166,439
Months	396	396	396	396	396	396	396	396	396

The table shows average slopes from monthly cross-section regressions to predict stock returns of U.S. banks between 1980 and 2014. All variables are trimmed at the 1% and 99% levels. Returns are monthly returns of the total return index, PII/A is Pre-impairment operating income divided by total assets, OI/A is Operating income divided by total assets, PTI/A is Pre-tax income divided by total assets, NI/E is Net income divided by book value of equity, LLP/A is loan loss provisions divided by total assets, LS is loan share, AD is asset diversification, DS is deposit share, BE/A is book equity divided by total assets, log(B/M) is the natural logarithm of book-to-market, log(ME) is the natural logarithm of market equity, $r_{0,1}$ is past performance measured at a horizon of one month, $r_{2,12}$ is past performance measured at a horizon of 12 to two months. p-values under parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 3.11: Average monthly returns for portfolios formed on one-way sorts - Value-weighted average stock returns

	(1)	(2)	(3)	(4)	(5)	(5)−(1)[a]	ANOVA[b]
PII/A	0.116	0.137	0.142	0.283	0.419	0.303*	0.011**
OI/A	0.165	0.197	0.169	0.270	0.297	0.133	0.222
PTI/A	0.174	0.211	0.177	0.266	0.270	0.097	0.351
NI/E	0.144	0.163	0.135	0.240	0.417	0.274*	0.032**
log(B/M)	0.346	0.186	0.213	0.165	0.189	−0.157	0.210
log(ME)	0.009	0.022	0.044	0.103	0.921	0.912***	0.000***
$r_{0,1}$	0.362	0.269	0.274	0.213	−0.020	−0.381***	0.004***
$r_{2,12}$	0.232	0.237	0.256	0.164	0.209	−0.023	0.660
LLP/A	0.075	0.121	0.164	0.356	0.382	0.307*	0.007***
LS	0.282	0.249	0.161	0.200	0.206	−0.076	0.466
AD	0.213	0.211	0.162	0.287	0.226	0.013	0.706
DS	0.690	0.191	0.099	0.068	0.049	−0.641***	0.000***
BE/A	0.397	0.328	0.217	0.098	0.058	−0.338***	0.002***

The table shows averages of monthly value-weight stock returns for each portfolio and for the hedged portfolio obtained from long-short positions in the extreme quantiles. The sample covers U.S. banks between 1980-2014. All variables are winsorised at the 1% and 99% levels. Average monthly returns are expressed in %; Returns are monthly returns of the total return index, PII/A is Pre-impairment operating income divided by total assets, OI/A is Operating income divided by total assets, PTI/A is Pre-tax income divided by total assets, NI/E is Net income divided by book value of equity, log(B/M) is the natural logarithm of book-to-market, log(ME) is the natural logarithm of market equity, $r_{0,1}$ is past performance measured at a horizon of one month, $r_{2,12}$ is past performance measured at a horizon of 12 to two months, LLP/A is loan loss provisions divided by total assets, LS is loan share, AD is asset diversification, DS is deposit share, BE/A is book equity divided by total assets. [a] *t*-test and significance; The null hypothesis is that the mean of long−short portfolios is zero. [b] *p*-values for the ANOVA test; The null hypothesis is equality of average monthly portfolio returns across quantile sorts for a given sort. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 3.12: Fama and MacBeth (1973) monthly cross-sectional regression - Smaller market capitalisations excluded from the sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PII/A	−0.071								
	(0.319)								
OI/A		0.030							
		(0.664)							
PTI/A			0.024						
			(0.737)						
NI/E				0.008					
				(0.246)					
LLP/A					-0.517^{**}				
					(0.010)				
LS						-0.006^{*}			
						(0.056)			
AD							0.006^{***}		
							(0.003)		
DS								0.004	
								(0.323)	
BE/A									−0.020
									(0.364)
log(B/M)	0.663^{***}	0.710^{***}	0.713^{***}	0.780^{***}	0.755^{***}	0.719^{***}	0.726^{***}	0.782^{***}	0.707^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(ME)	0.096	0.091	0.092	0.087	0.103^{*}	0.097	0.100	0.112^{*}	0.092
	(0.121)	(0.142)	(0.138)	(0.157)	(0.094)	(0.119)	(0.105)	(0.066)	(0.129)
$r_{0,1}$	-0.106^{***}	-0.106^{***}	-0.106^{***}	-0.106^{***}	-0.108^{***}	-0.106^{***}	-0.106^{***}	-0.107^{***}	-0.106^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$r_{2,12}$	0.002	0.001	0.001	0.001	0.000	0.001	0.001	0.001	0.001
	(0.482)	(0.605)	(0.602)	(0.763)	(0.977)	(0.710)	(0.720)	(0.664)	(0.631)
Avg. R^2	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11
Obs.	152,334	152,334	152,334	152,334	152,334	152,334	152,334	152,334	152,334
Months	396	396	396	396	396	396	396	396	396

The table shows average slopes from monthly cross-section regressions to predict stock returns of U.S. banks between 1980 and 2014. All variables are winsorised at the 1% and 99% levels. Observations included in the small (1) portfolio formed on market capitalisation are excluded from the sample. Observations included in the small (1) portfolio formed on market capitalisation are excluded from the sample. Returns are monthly returns of the total return index, PII/A is Pre-impairment operating income divided by total assets, OI/A is Operating income divided by total assets, PTI/A is Pre-tax income divided by total assets, NI/E is Net income divided by book value of equity, LLP/A is loan loss provisions divided by total assets, LS is loan share, AD is asset diversification, DS is deposit share, BE/A is book equity divided by total assets, log(B/M) is the natural logarithm of book-to-market, log(ME) is the natural logarithm of market equity, $r_{0,1}$ is past performance measured at a horizon of one month, $r_{2,12}$ is past performance measured at a horizon of 12 to two months. p-values under parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 3.13: Fama and MacBeth (1973) monthly cross-sectional regression - Only smaller market capitalisations included

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PII/A	0.065								
	(0.685)								
OI/A		0.286^{**}							
		(0.047)							
PTI/A			0.342^{**}						
			(0.016)						
NI/E				0.029^{**}					
				(0.021)					
LLP/A					-1.181^{***}				
					(0.000)				
LS						-0.008			
						(0.112)			
AD							0.006^{*}		
							(0.063)		
DS								0.021^{**}	
								(0.022)	
BE/A									0.024
									(0.361)
log(B/M)	1.053^{***}	1.110^{***}	1.104^{***}	1.064^{***}	1.197^{***}	1.111^{***}	1.141^{***}	1.130^{***}	1.134^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(ME)	0.642^{***}	0.551^{***}	0.523^{***}	0.499^{***}	0.597^{***}	0.694^{***}	0.701^{***}	0.798^{***}	0.694^{***}
	(0.000)	(0.000)	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$r_{0,1}$	-0.114^{***}	-0.117^{***}	-0.117^{***}	-0.116^{***}	-0.112^{***}	-0.109^{***}	-0.111^{***}	-0.108^{***}	-0.109^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$r_{2,12}$	0.007^{*}	0.005	0.005	0.005	0.002	0.006	0.006^{*}	0.006	0.005
	(0.064)	(0.129)	(0.155)	(0.121)	(0.527)	(0.107)	(0.081)	(0.115)	(0.155)
Avg. R^2	0.18	0.18	0.18	0.19	0.19	0.17	0.17	0.17	0.17
Obs.	38,270	38,270	38,270	38,270	38,270	38,270	38,270	38,270	38,270
Months	396	396	396	396	396	396	396	396	396

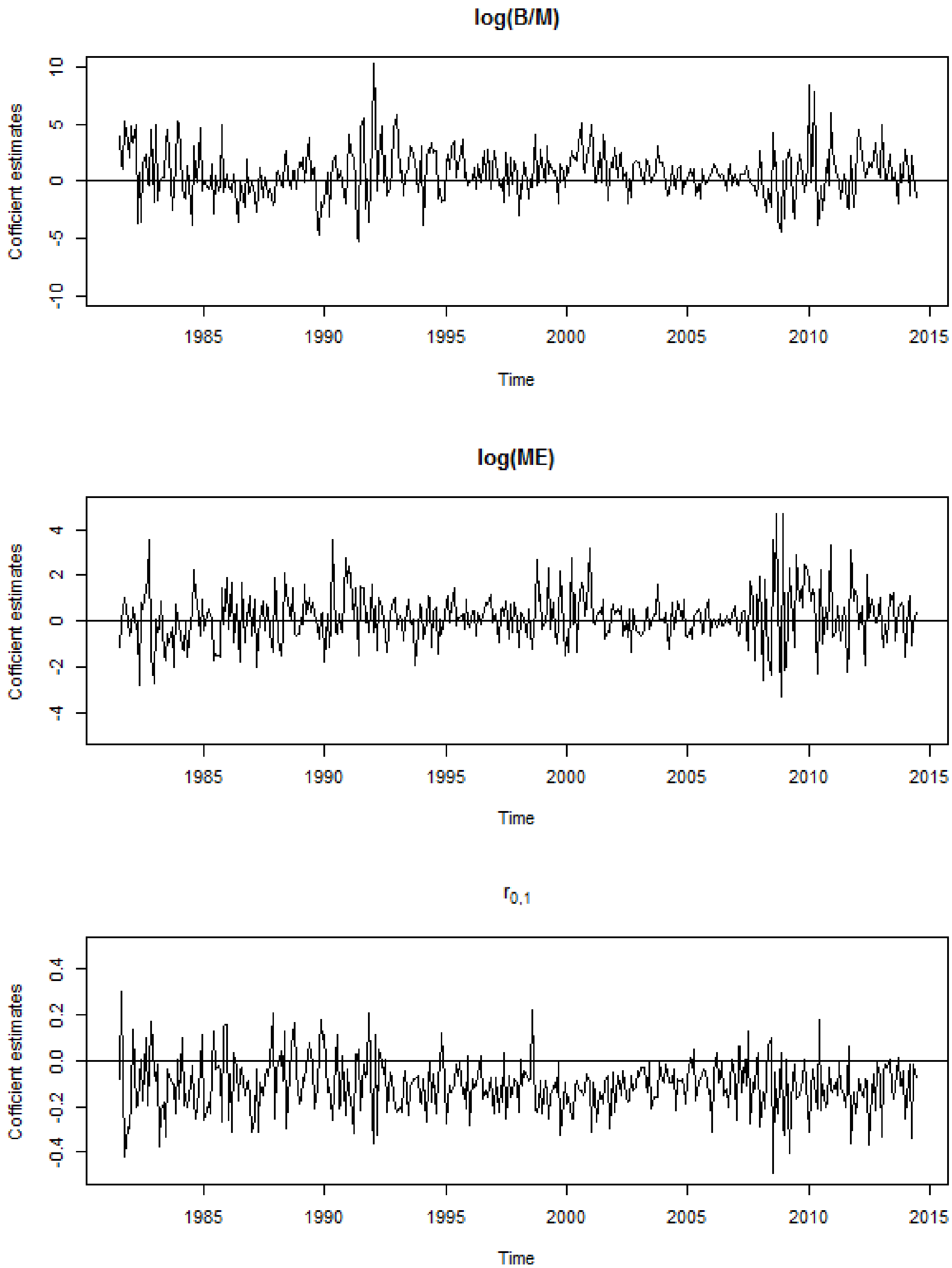
The table shows average slopes from monthly cross-section regressions to predict stock returns of U.S. banks between 1980 and 2014. All variables are winsorised at the 1% and 99% levels. Only observations included in the small (1) portfolio formed on market capitalisation are included in the sample. Returns are monthly returns of the total return index, PII/A is Pre-impairment operating income divided by total assets, OI/A is Operating income divided by total assets, PTI/A is Pre-tax income divided by total assets, NI/E is Net income divided by book value of equity, LLP/A is loan loss provisions divided by total assets, LS is loan share, AD is asset diversification, DS is deposit share, BE/A is book equity divided by total assets, log(B/M) is the natural logarithm of book-to-market, log(ME) is the natural logarithm of market equity, $r_{0,1}$ is past performance measured at a horizon of one month, $r_{2,12}$ is past performance measured at a horizon of 12 to two months. p-values under parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 3.14: Time series regression of long−short portfolios' returns on the four-factor model of Carhart (1997) - Value-weighted average stock returns

Ranked by	α	β_{MKT}	β_{SMB}	β_{HML}	β_{UMD}	R^2	Months
PII/A	0.05 (0.71)	0.38 (0.00)***	0.00 (0.92)	0.34 (0.00)***	−0.17 (0.00)***	0.41	396
OI/A	0.06 (0.52)	0.18 (0.00)***	−0.07 (0.04)**	0.12 (0.00)***	−0.13 (0.00)***	0.25	396
PTI/A	0.04 (0.65)	0.14 (0.00)***	−0.03 (0.35)	0.08 (0.02)**	−0.10 (0.00)***	0.17	396
NI/E	0.06 (0.66)	0.35 (0.00)***	−0.11 (0.02)**	0.23 (0.00)***	−0.13 (0.00)***	0.32	396
log(B/M)	0.01 (0.95)	−0.25 (0.00)***	−0.06 (0.09)*	−0.21 (0.00)***	0.13 (0.00)***	0.35	396
log(ME)	0.16 (0.44)	0.98 (0.00)***	−0.05 (0.49)	0.72 (0.00)***	−0.20 (0.00)***	0.58	396
$r_{0,1}$	−0.32 (0.03)**	−0.04 (0.20)	0.00 (0.98)	−0.01 (0.82)	−0.05 (0.09)*	0.01	396
$r_{2,12}$	−0.13 (0.26)	0.02 (0.45)	−0.07 (0.08)*	0.04 (0.39)	0.15 (0.00)***	0.09	396
LLP/A	0.03 (0.83)	0.44 (0.00)***	−0.04 (0.36)	0.38 (0.00)***	−0.22 (0.00)***	0.46	396
LS	0.02 (0.91)	−0.17 (0.00)***	−0.11 (0.01)**	−0.24 (0.00)***	0.19 (0.00)***	0.23	396
AD	−0.05 (0.71)	0.12 (0.00)***	0.11 (0.01)**	0.24 (0.00)***	−0.18 (0.00)***	0.21	396
DS	−0.10 (0.58)	−0.73 (0.00)***	0.01 (0.85)	−0.59 (0.00)***	0.21 (0.00)***	0.54	396
BE/A	−0.12 (0.19)	−0.32 (0.00)***	0.13 (0.00)***	−0.12 (0.00)***	0.02 (0.24)	0.38	396

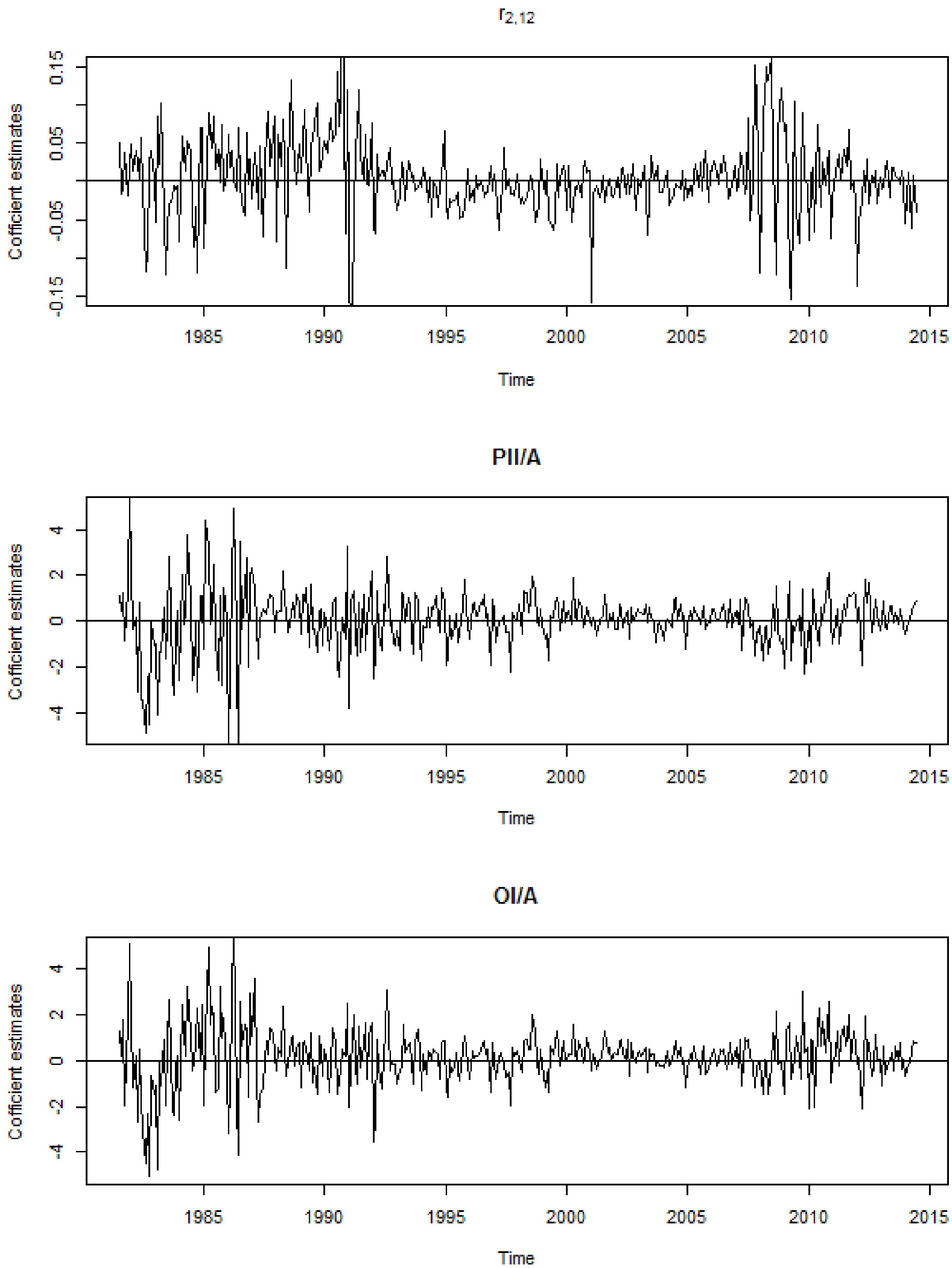
The table provides results from times series regressions of average value-weight returns from long−short portfolios for U.S. banks between 1980-2014 on a four-factor model. α represents the excess returns, i.e. returns above and beyond that suggested by the four-factor model of Carhart (1997). Returns are monthly returns of the total return index, PII/A is Pre-impairment operating income divided by total assets, OI/A is Operating income divided by total assets, PTI/A is Pre-tax income divided by total assets, NI/E is Net income divided by book value of equity, log(B/M) is the natural logarithm of book-to-market, log(ME) is the natural logarithm of market equity, $r_{0,1}$ is past performance measured at horizon of one month, $r_{2,12}$ is past performance measured at horizon of 12 to two months, LLP/A is loan loss provisions divided by total assets, LS is loan share, AD is asset diversification, DS is deposit share, BE/A is book equity divided by total assets. p-values under parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Figure 3.2: Monthly coefficient estimates from the first step of the Fama and MacBeth (1973) procedure



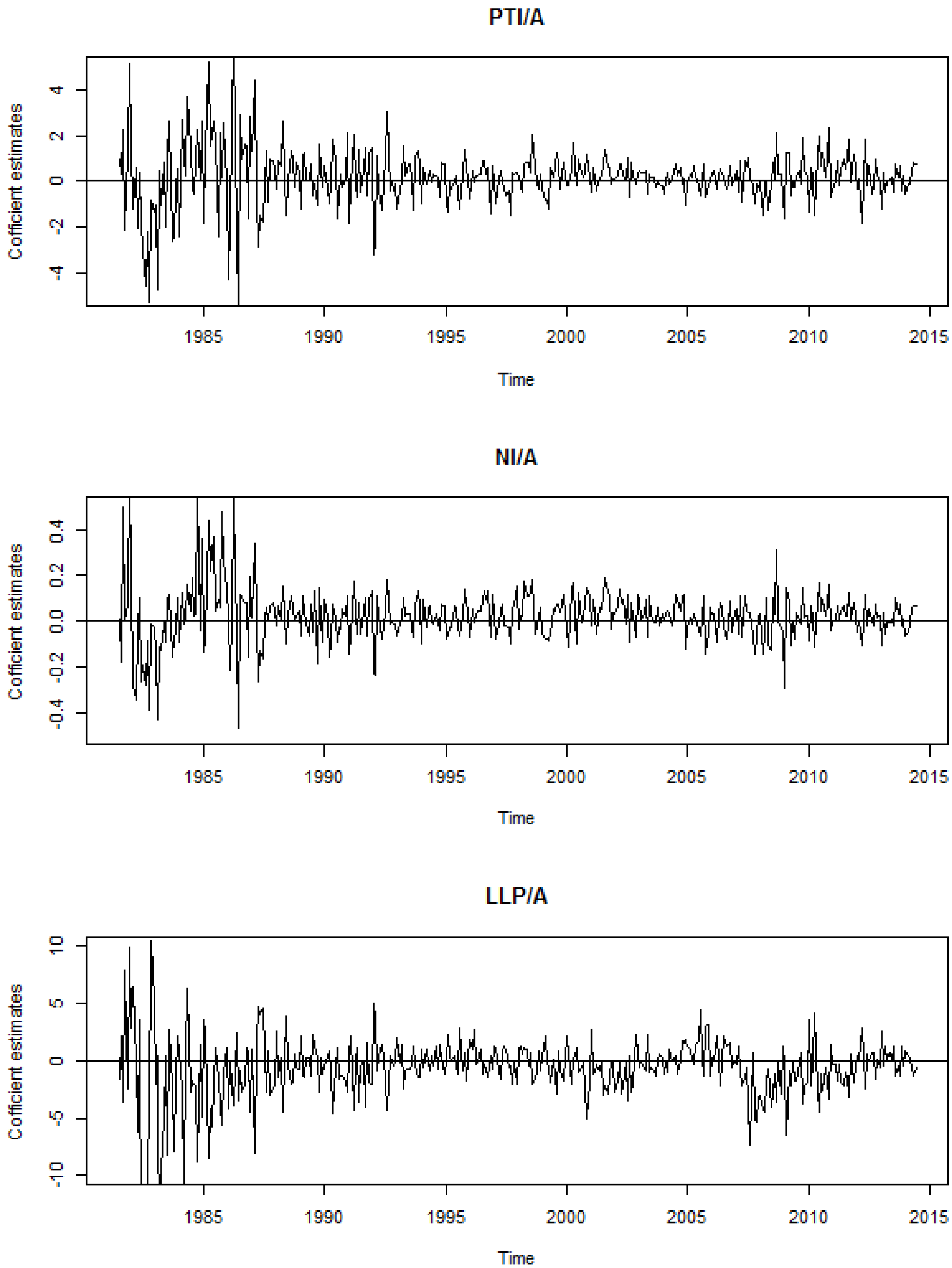
The figure shows the monthly coefficient estimates of the first step of the Fama and MacBeth (1973) procedure displayed on Table 3.6. The coefficient estimates of the control variables log(B/M), log(ME), $r_{0,1}$ and $r_{2,12}$ come from the first (1) specification.

Figure 3.2: Monthly coefficient estimates from the first step of the Fama and MacBeth (1973) procedure (continued)



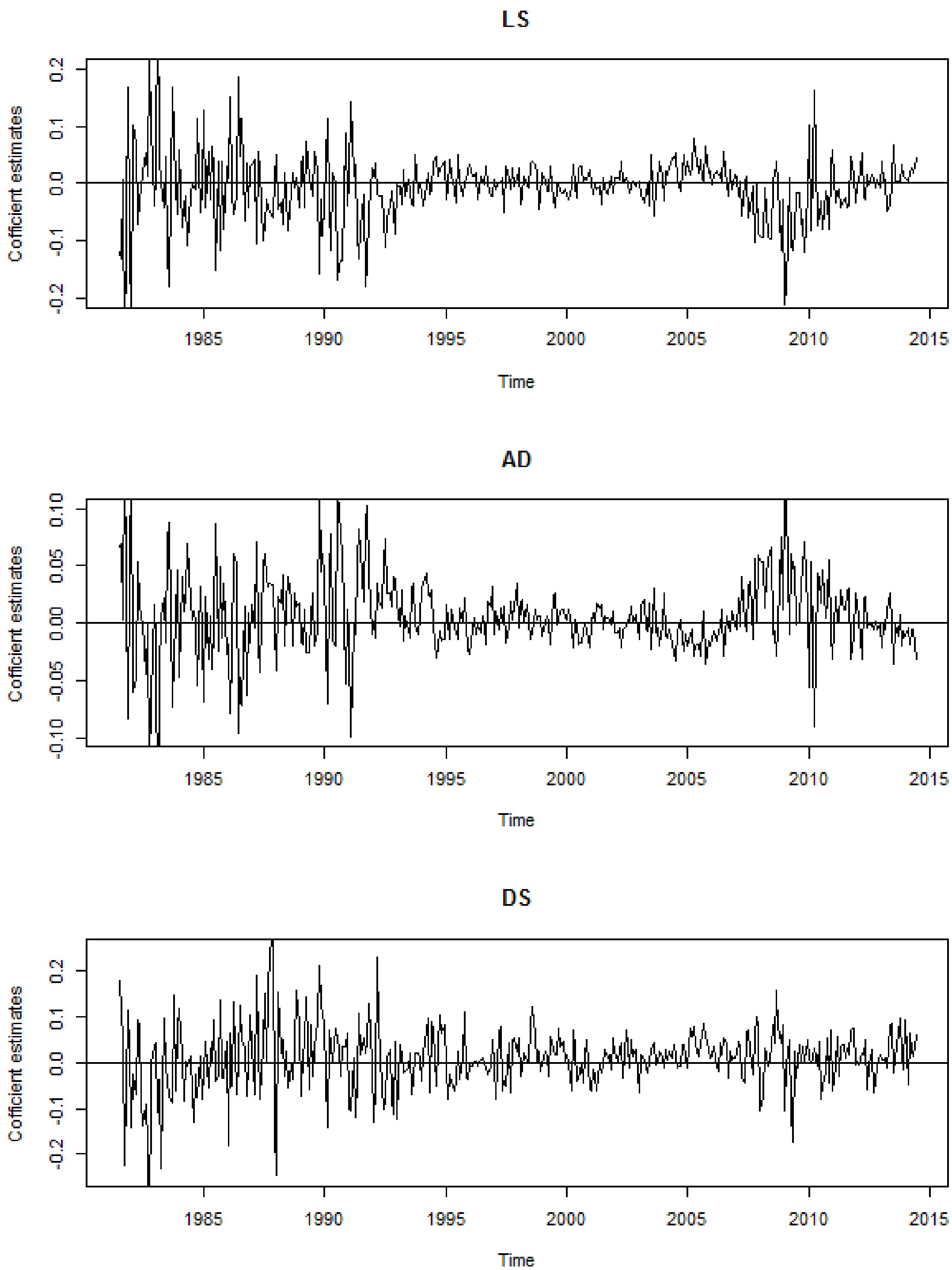
The figure shows the monthly coefficient estimates of the first step of the Fama and MacBeth (1973) procedure displayed on Table 3.6. The coefficient estimates of the control variables log(B/M), log(ME), $r_{0,1}$ and $r_{2,12}$ come from the first (1) specification.

Figure 3.2: Monthly coefficient estimates from the first step of the Fama and MacBeth (1973) procedure (continued)



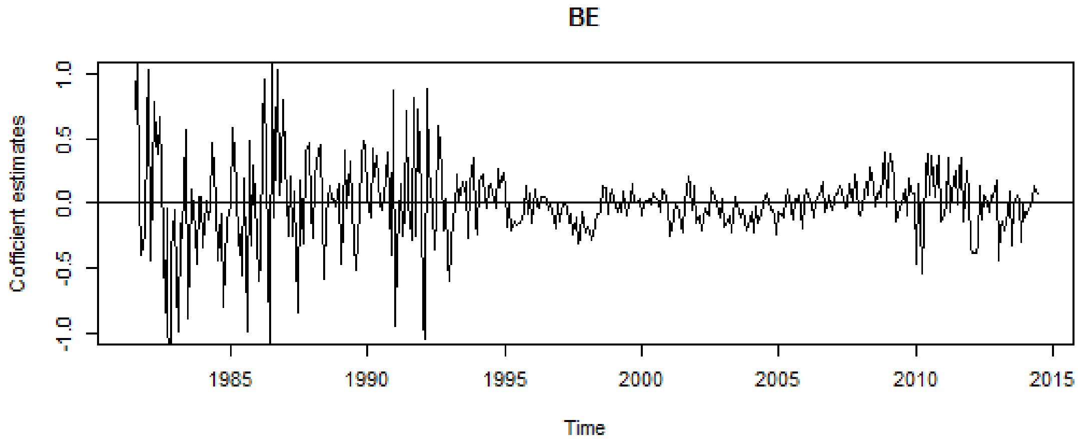
The figure shows the monthly coefficient estimates of the first step of the Fama and MacBeth (1973) procedure displayed on Table 3.6. The coefficient estimates of the control variables log(B/M), log(ME), $r_{0,1}$ and $r_{2,12}$ come from the first (1) specification.

Figure 3.2: Monthly coefficient estimates from the first step of the Fama and MacBeth (1973) procedure (continued)



The figure shows the monthly coefficient estimates of the first step of the Fama and MacBeth (1973) procedure displayed on Table 3.6. The coefficient estimates of the control variables log(B/M), log(ME), $r_{0,1}$ and $r_{2,12}$ come from the first (1) specification.

Figure 3.2: Monthly coefficient estimates from the first step of the Fama and MacBeth (1973) procedure (continued)



The figure shows the monthly coefficient estimates of the first step of the Fama and MacBeth (1973) procedure displayed on Table 3.6. The coefficient estimates of the control variables log(B/M), log(ME), $r_{0,1}$ and $r_{2,12}$ come from the first (1) specification.

Table 3.15: Fama and MacBeth (1973) monthly cross-sectional regression 1981-1998

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PII/A	−0.024								
	(0.840)								
OI/A		0.121							
		(0.264)							
PTI/A			0.154						
			(0.174)						
NI/E				0.023**					
				(0.026)					
LLP/A					−0.862***				
					(0.001)				
LS						−0.008			
						(0.113)			
AD							0.008***		
							(0.006)		
DS								0.006	
								(0.318)	
BE/A									0.000***
									(0.000)
log(B/M)	0.710***	0.766***	0.787***	0.843***	0.807***	0.755***	0.772***	0.788***	0.772***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(ME)	0.123*	0.129*	0.131*	0.119	0.149**	0.127*	0.131*	0.147**	0.113
	(0.085)	(0.071)	(0.067)	(0.101)	(0.036)	(0.071)	(0.061)	(0.026)	(0.104)
$r_{0,1}$	−0.097***	−0.098***	−0.098***	−0.099***	−0.097***	−0.096***	−0.098***	−0.097***	−0.097***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$r_{2,12}$	0.009**	0.008**	0.008**	0.007*	0.007*	0.008**	0.008**	0.008**	0.008**
	(0.024)	(0.028)	(0.030)	(0.067)	(0.074)	(0.031)	(0.035)	(0.033)	(0.038)
Avg. R^2	0.11	0.12	0.12	0.12	0.12	0.11	0.11	0.11	0.11
Obs.	56,334	56,334	56,334	56,334	56,334	56,334	56,334	56,334	56,334
Months	210	210	210	210	210	210	210	210	210

The table shows average slopes from monthly cross-section regressions to predict stock returns of U.S. banks between 1981 and 1998. All variables are winsorised at the 1% and 99% levels. Returns are monthly returns of the total return index, PII/A is Pre-impairment operating income divided by total assets, OI/A is Operating income divided by total assets, PTI/A is Pre-tax income divided by total assets, NI/E is Net income divided by book value of equity, LLP/A is loan loss provisions divided by total assets, LS is loan share, AD is asset diversification, DS is deposit share, BE/A is book equity divided by total assets, log(B/M) is the natural logarithm of book-to-market, log(ME) is the natural logarithm of market equity, $r_{0,1}$ is past performance measured at a horizon of one month, $r_{2,12}$ is past performance measured at a horizon of 12 to two months. p-values under parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 3.16: Fama and MacBeth (1973) monthly cross-sectional regression 1999-2014

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PII/A	0.102*								
	(0.069)								
OI/A		0.221***							
		(0.000)							
PTI/A			0.207***						
			(0.000)						
NI/E				0.021***					
				(0.000)					
LLP/A					−0.629***				
					(0.000)				
LS						−0.006*			
						(0.056)			
AD							0.004**		
							(0.029)		
DS								0.014***	
								(0.000)	
BE/A									−0.003
									(0.802)
log(B/M)	0.760***	0.897***	0.894***	0.864***	0.825***	0.720***	0.728***	0.827***	0.724***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log(ME)	0.251***	0.242***	0.243***	0.237***	0.285***	0.263***	0.262***	0.312***	0.265***
	(0.006)	(0.008)	(0.007)	(0.009)	(0.002)	(0.004)	(0.005)	(0.001)	(0.004)
$r_{0,1}$	−0.118***	−0.119***	−0.120***	−0.120***	−0.120***	−0.119***	−0.119***	−0.119***	−0.119***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$r_{2,12}$	0.001	0.000	0.000	−0.001	−0.002	0.000	0.000	0.000	0.001
	(0.794)	(0.918)	(0.911)	(0.878)	(0.637)	(0.965)	(0.998)	(0.892)	(0.824)
Avg. R^2	0.08	0.09	0.09	0.09	0.09	0.09	0.08	0.08	0.09
Obs.	134,270	134,270	134,270	134,270	134,270	134,270	134,270	134,270	134,270
Months	186	186	186	186	186	186	186	186	186

The table shows average slopes from monthly cross-section regressions to predict stock returns of U.S. banks between 1999 and 2014. All variables are winsorised at the 1% and 99% levels. Returns are monthly returns of the total return index, PII/A is Pre-impairment operating income divided by total assets, OI/A is Operating income divided by total assets, PTI/A is Pre-tax income divided by total assets, NI/E is Net income divided by book value of equity, LLP/A is loan loss provisions divided by total assets, LS is loan share, AD is asset diversification, DS is deposit share, BE/A is book equity divided by total assets, log(B/M) is the natural logarithm of book-to-market, log(ME) is the natural logarithm of market equity, $r_{0,1}$ is past performance measured at a horizon of one month, $r_{2,12}$ is past performance measured at a horizon of 12 to two months. p-values under parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 3.17: Time series regression of long−short portfolios' returns on the three-factor model of Fama and French (1993)

Ranked by	α	β_{MKT}	β_{SMB}	β_{HML}	R^2	Months
PII/A	−0.04 (0.79)	0.08 (0.02)**	−0.10 (0.06)*	0.08 (0.15)	0.03	396
OI/A	0.27 (0.10)	−0.08 (0.04)**	−0.18 (0.00)***	−0.09 (0.11)	0.04	396
PTI/A	0.30 (0.07)*	−0.10 (0.01)**	−0.18 (0.00)***	−0.12 (0.05)**	0.05	396
NI/E	0.28 (0.09)*	0.03 (0.40)	−0.26 (0.00)***	−0.08 (0.18)	0.05	396

The table provides results from times series regressions of average equal-weight returns from long−short portfolios for U.S. banks between 1980-2014 on a three-factor model. α represents the excess returns, i.e. returns above and beyond that suggested by the three-factor model of Fama and French (1993). Returns are monthly returns of the total return index, PII/A is Pre-impairment operating income divided by total assets, OI/A is Operating income divided by total assets, PTI/A is Pre-tax income divided by total assets, NI/E is Net income divided by book value of equity, log(B/M) is the natural logarithm of book-to-market, log(ME) is the natural logarithm of market equity, $r_{0,1}$ is past performance measured at horizon of one month, $r_{2,12}$ is past performance measured at horizon of 12 to two months, LLP/A is loan loss provisions divided by total assets, LS is loan share, AD is asset diversification, DS is deposit share, BE/A is book equity divided by total assets. p-values under parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 3.18: Fama and MacBeth (1973) monthly cross-sectional regression of returns for each size quintile

	(1)	(2)	(3)	(4)	(5)
PII/A	0.065	−0.115	−0.022	−0.161	0.045
	(0.685)	(0.374)	(0.890)	(0.235)	(0.816)
log(B/M)	1.053***	0.780***	0.887***	0.654***	0.603***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)
log(ME)	0.642***	0.421*	0.256	0.158	−0.096
	(0.000)	(0.080)	(0.451)	(0.477)	(0.314)
$r_{0,1}$	−0.114***	−0.108***	−0.096***	−0.117***	−0.121***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$r_{2,12}$	0.007*	0.000	0.001	0.002	0.002
	(0.064)	(0.948)	(0.759)	(0.577)	(0.688)
Avg. R^2	0.18	0.16	0.17	0.18	0.21
Obs.	38,270	38,131	38,102	38,140	37,961
Months	396	396	396	396	396

The table shows average slopes from monthly cross-section regressions to predict stock returns of U.S. banks between 1980 and 2014. We run separate regression for each size portfolio, (1) being the smallest and (5) the largest portfolio formed on market capitalisation. All variables are winsorised at the 1% and 99% levels. Returns are monthly returns of the total return index, PII/A is Pre-impairment operating income divided by total assets, log(B/M) is the natural logarithm of book-to-market, log(ME) is the natural logarithm of market equity, $r_{0,1}$ is past performance measured at a horizon of one month, $r_{2,12}$ is past performance measured at a horizon of 12 to two months. p-values under parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Chapter 4

Earnings Management in Banking: Dissecting the Kink

Earnings Management in Banking: Dissecting the Kink

Nicolas Guerry*

January 25, 2016

Abstract

This paper uses a distributional approach to explore earnings management in banking. Starting from a smooth pre-managed distribution, earnings measures further down the income statement show the progressive apparition of a kink around zero earnings. The magnitude of the kink culminates in the distribution of net income. A closer investigation reveals that banks with relatively high pre-managed earnings are characterised by significantly higher impairment charges on loans, securities, and other credits and higher tax expenses relative to banks with smaller pre-managed earnings. Differences relating to impairment charges are likely to reflect at least some degree of earnings management since banks with small pre-managed earnings may be tempted to understate these charges to avoid reporting losses. In contrast, differences in tax expenses are more difficult to reconcile with an earnings management explanation given the positive relationship between earnings and tax expenses. Though a whole stream of the literature associates the kink with earnings management, it appears to be only a partial explanation.

Keywords: Earnings management, Banks, Earnings distribution, Discretionary accruals, Financial performance.

JEL Classification Numbers: G21, G28, M41.

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4.1. Introduction

Research has shown that accounting numbers, and earnings in particular, have informational content for various stakeholders such as investors, financial analysts, or regulators (Degeorge et al., 1999; Hayn, 1995). Yet, earnings management may cause reported earnings to not properly reflect the underlying economic reality. According to the earnings management literature, insiders, and managers in particular, use their discretion in accounting to overstate the true level of earnings reported to the external audience in order to hide unfavourable figures, or to smooth out their fluctuations. Doing so should notably bolster investors' interest and affect stock prices, and with them managers' own wealth, e.g. through option and stock compensation (Cornett, McNutt, & Tehranian, 2009; Degeorge et al., 1999).[1] Earnings management may also be the result of perceived bankruptcy concerns (Fonseca & Gonzalez, 2008; Laeven & Majnoni, 2003), or serve the purpose of window dressing of financial statements prior to public securities offerings (Cornett et al., 2009).

Banks, and more generally financial firms, are often excluded from earnings management studies (Shen & Chih, 2005). This exclusion lies in the high degree of regulation in the banking industry, the difficulty associated with estimating a bank's discretionary accruals, and industry-specific characteristics that make banks more opaque than firms in other industries. Such fundamental differences require a separate analysis from the nonfinancial industry (Bouvatier, Lepetit, & Strobel, 2014). While some aspects of earnings management have been explored in the banking industry (e.g. presence of a kink in the distribution of reported earnings, see Shen and Chih (2005)), others remain largely unexplored.

Due to the intermediation function fulfilled by banks, analysing earnings management within the banking industry is of importance since this practice compromises the faithful representation of underlying economic condition and riskiness. This may in turn reduce substantially the ability of stakeholders (e.g. regulators, supervisors, shareholders, debtholders) to properly monitor banks. The banking literature posits that informational transparency plays an important role since it allows market participants to monitor and discipline excessive risk-taking. The availability of timely,

[1] One of the motivation behind earnings management is the conjecture that investors rely on simple low-cost heuristics, such as earnings benchmarks, in firm valuation (Beatty et al., 2002).

consistent, and reliable information on banks' financial performance is particularly crucial (Bushman & Williams, 2012). As witnessed by the global financial crisis, the likelihood of bank failures increases curtailing economic development, and welfare more generally, when insiders exploit banks for their own purposes (Bouvatier et al., 2014; Bushman & Williams, 2012). In addition, incentives to practice earnings management in order to improve risk perception may be particularly strong given the high degree of regulation in banking.[2]

This paper explores earnings management in banking using a distributional approach for a sample of international banks between 1999-2013. We start by analysing the presence of a king around zero earnings. We find convincing evidence indicating the presence of a kink in the distribution of Net income and therefore confirm findings of Shen and Chih (2005) for earlier years (1993-1999). In a second step, we show that the banking industry is characterised by the presence of a smooth pre-managed earnings distribution (Pre-impairment operating income), thus echoing findings from Dechow et al. (2003) for the nonfinancial industry. In order to examine which components of earnings are managed and contribute to the kink, we analyse different earnings streams that occur between these two earnings measures. This research design has, to the best of our knowledge, never been implemented in a study focusing on earnings management within the banking industry.

Our study shows that the distribution of Net income is asymmetrically shifted to the left relative to the distribution of Pre-impairment operating profit, and this causes the kink. This asymmetrical shift affects mostly banks with positive earnings, while the portion of the distribution located left to zero is largely unaffected. More specifically, banks with relatively high pre-managed earnings are disproportionally shifted to the left compared to banks with smaller positive earnings. This partial shift reflects higher earnings streams, that reduce more heavily reported earnings, among banks with higher pre-managed earnings. This finding is compatible with a loss avoidance story predicting that firms manage earnings in order to report profits, even small ones. Compared to banks with higher pre-managed earnings that can afford stronger hits, banks with modest earnings are more likely to understate subsequent earnings streams to avoid reporting losses. This difference

[2]Others argue that earnings management in banking is a desirable feature under certain certain circumstances, e.g. to avoid bank runs after significant losses. Iannotta and Kwan (2014) noted that regulators may have a bias in favour of earnings management through loan losses provisions. Overestimating loan loss provisions in good times may for example increase the capacity of banks to absorb losses from future credit impairments in bad times.

in earnings streams among these two earnings groups result in an accumulation of observations in the small earnings area causing the kink.

The decomposition of total earnings streams shows that banks with higher pre-managed earnings have on average (1) higher impairment charges on loans, securities, and other credits as well as (2) higher tax expenses relative to smaller earnings banks. We show that both earnings streams are responsible for the apparition of the kink and its subsequent reinforcement. In the light of these results, earnings management appears to be a plausible explanation for the kink, but only a partial one. The use of impairment charges for earnings management purposes is well-known and has been widely documented in the banking literature. Thus, the difference in terms of impairment charges among earnings groups is likely to reflect at least some degree of earnings management. It is, however, less likely that earnings management is the main driver of the difference relating to tax expenses. Given that tax expenses are largely a positive function of earnings, the fact that banks with higher earnings have higher tax expenses can rationally be explained without an earnings management story. Thus, our results suggest that earnings management is only a partial explanation for the kink, though a whole stream of the literature attributes the presence of this irregularity to earnings management without further investigation.

The remainder of this paper is structured as follows. In Section 4.2, we briefly review the relevant literature with special focus on earnings management in general, the main research designs used to investigate earnings management, the distributional approach, and the specificity of earnings management in banking. In Section 4.3, we discuss the data and the methodology used for the empirical part of this study. In Section 4.4, we analyse distributions from several earnings measures and investigate more closely the presence of an irregularity around zero earnings. In Section 4.5, we investigate what particular earnings streams are responsible for the kink, and whether earnings management is the cause of the kink. In Section 4.6, we conduct several robustness tests of our results. Section 4.7 concludes.

4.2. Relevant literature

Extensive literature reviews on earnings management have been provided by Schipper (1989), Healy and Wahlen (1999), Fields, Lys, and Vincent (2001), and Verbruggen, Christiaens, and Milis (2008). Another literature review focusing on the characteristics of commonly applied designs in the earnings management literature has been provided by McNichols (2000).

Earnings management

Managers use accounting and reporting to communicate information on the firm performance to various external stakeholders (e.g. providers of debt, equity, and labour, auditors, financial analysts, bond rating agencies, regulators, suppliers, customers). If adequately used, financial reporting can enable the best-performing firms to distinguish themselves from poor performers and should therefore facilitate efficient resource allocation by stakeholders. To be able to fulfil this role, released accounting information should reflect true differences in firms' economic positions and performance (Healy & Wahlen, 1999). Accounting and financial reporting are, however, no exact science and contain significant elements of subjectivity. Since auditing is not perfect, this situation creates opportunities for managers to use discretionary judgement in order to hide unfavourable earnings realisations, or, in other words, for practising *earnings management*. Managers' judgement is notably required in order to estimate various future economic events that are reflected in financial statements, e.g. expected lives and salvage values of long-term assets, obligations for pension benefits and other post-employment benefits, or losses from bad debts and asset impairments (Healy & Wahlen, 1999).

According to Healy and Wahlen (1999), earnings management consists in managers choosing reporting methods and estimates that do not reflect the true underlying economic performance of their firms in order to mislead some stakeholders and/or to generate some form of private benefit. Concrete motivations for exercising earnings management include, but are not limited to: window-dressing of financial statements prior to public securities offerings; management buyouts; corporate managers' compensation and job security; lending contracts covenants; and regulatory purposes (e.g. avoid violating regulations or increase regulatory benefits).[3] Moreover, the widespread use of accounting information by investors and financial analysts to help value stocks also creates incentives for managers to manipulate earnings in an attempt to influence stock price performance (Healy & Wahlen, 1999).

Commonly applied research designs

Three main research designs prevail in the earnings management literature. The first approach attempts to identify discretionary accruals based on the relation between total accruals and hypothesised explanatory factors. Accruals are non-cash transactions included in financial reporting. Because they consist in non-cash transaction, accruals, or at least some of these accruals labelled as "discretionary", are assumed to contain some degree of subjectivity that can be used for earnings management purposes. Consequently, "normal" accruals, normal in the sense of accruals in the absence of earnings management, are often assumed to be unknown (McNichols, 2000).

The widely used (modified) Jones (1991) model is employed to estimate these normal accruals. More specifically, normal accruals are estimated from elements such as firm assets, property, plant, and equipment, or change in sales. "Abnormal" or discretionary accruals are the difference between actual accruals and the estimated accruals from the modified Jones model. Firms with consistently large discretionary accruals are deemed more likely to manipulate earnings (Cohen et al., 2014). Studies using this design usually investigate the presence of earnings management by examining whether discretionary accruals, as proxy for the degree of earnings management, are systematically related to potential drivers of earnings management activities.

The second research design consists in modelling a specific accrual (e.g. residual provision for bad debt; see McNichols (2000)). Studies employing this approach often focus on industry settings in which a single accrual (e.g. provision for loan losses in the banking industry) is sizable and requires substantial judgement. As with aggregate accruals studies, a key aspect of the research design task is modelling the behaviour of each specific accrual to identify its discretionary and nondiscretionary components.

[3]For more details on motives for earnings management, see e.g. Verbruggen et al. (2008, pp. 5-8), "4. Motives for earnings management".

Finally, a third method commonly used is the distributional approach. With this approach, researchers analyse the distribution of earnings around certain thresholds, typically zero earnings. Absent earnings management, this approach assumes a smooth probability distribution around zero earnings in which the expected number of observations in an interval is the average of the two adjacent intervals. Discontinuity around the thresholds are typically interpreted as evidence of earnings management. Studies using this research design typically investigate whether earnings management is present in the sample analysed as well as the magnitude of earnings management (Verbruggen et al., 2008). Because the distributional approach is the approach used in this study, it will be further discussed in the following.

The distributional approach

Studies such as Hayn (1995), Burgstahler and Dichev (1997), Degeorge et al. (1999), or Dechow et al. (2003) have reported the existence of a relatively smooth, bell-shaped distribution of reported earnings across most of the earnings spectrum, with one notable exception: the presence of an irregularity around zero earnings that is commonly labelled as “kink”.[4] This kink is typically seen as evidence that too few firms report small losses and too many firms report small profits. In other words, it is seen as evidence that the frequency of small profit firms is abnormally high relative to the frequency of small loss firms. The kink is commonly interpreted as evidence suggesting the presence of earnings management.

[**Figure 4.1 about here**]

[**Figure 4.2 about here**]

The empirical literature assumes that managers take as given an accounting target and manage earnings in response (Schipper, 1989). Reporting a profit, even a small one, is often assumed to

[4] We report the histograms displayed by Burgstahler and Dichev (1997) and Dechow et al. (2003) on Figures 4.1 and 4.2.

be the accounting target in question (loss avoidance hypothesis, see e.g. Dechow et al. (2003)). Consequently, reaching at least the zero earnings benchmark is seen as an important motivation behind earnings management.[5] As a result, if a kink around zero is reported in the distribution of reported earnings, it is typically interpreted as evidence that a certain number of firms in the sample use earnings management in order to avoid reporting negative profits.

The work of Dechow et al. (2003) is of particular interest for this study. Not only did the authors confirm the existence of a kink around zero earnings in the distribution of reported earnings, but they also showed the existence of a smooth "pre-managed" earnings distribution with no sign of irregularity around zero earnings. They further compared earnings streams that occur between the smooth pre-managed earnings distribution and the kinked distribution of reported earnings in order to investigate whether earnings management was responsible for the apparition of the kink. They hypothesised that, in order to avoid a loss, firms with small pre-managed losses would boost earnings in order to report a profit, resulting in too few firms reporting small losses and too many firms reporting small profits. They found that firms with small pre-managed losses had significantly higher earnings streams compared to all other firms. However, they found no significant difference in earnings streams between small loss firms and small profit firms. While they conceded that the first finding was consistent with small profit firms engaging in earnings management, they concluded from the second finding that the kink was not explained by earnings management since both sets of firms have a similar proportion of positive discretionary accruals. The authors concluded that this result left open the question of what causes the kink.

Earnings management in banking

Banks are important for the economy due to their intermediation function. For this reason, it is important for various stakeholders (shareholders, debtholders, regulators, supervisors) to have

[5] According to Degeorge et al. (1999), there is an important psychological distinction between reporting positive and negative profits. Burgstahler and Dichev (1997) further underlined the existence of anecdotal evidence of incentives to report positive earnings. The literature further underlines the role of reported earnings to communicate information to external stakeholders. For example, results from a survey conducted by Graham, Harvey, and Rajgopal (2005) that asked CFOs to describe their choices related to reporting accounting numbers and voluntary disclosures revealed that CFOs believed that earnings, and not cash flows, were the key metrics considered by outsiders. In addition, the same study revealed that meeting or exceeding benchmarks (e.g. positive earnings) is very important.

access to faithful information on a bank's underlying economic condition and riskiness. In order to effectively monitor and discipline banks, the banking literature posits that informational transparency is crucial. Yet, earnings management is likely to impede information transparency by introducing a bias in reported financial performance.

As underlined by Shen and Chih (2005), financial institutions are often excluded from earnings management studies (e.g. Burgstahler and Dichev (1997); Dechow et al. (2003); DeFond and Subramanyam (1998)). We briefly review some of the reasons advanced in the literature. Financial institutions, and banks in particular, are subject to a high level of regulations that can affect incentives to avoid reported losses (Shen & Chih, 2005). In addition, several ratios (e.g. equity, non-performing loans) are strictly scrutinised and regulated, and earnings management is a technique used by banks to avoid violating regulations (Shen & Chih, 2005). Moreover, the estimation of discretionary accruals, seen as crucial for the analysis of earnings management of nonfinancial firms, can be problematic in the banking industry (DeFond & Subramanyam, 1998). Futhermore, the particular characteristics of banks (financial structure, higher leverage) makes them inherently more opaque than other firms and requires a separate analysis (Bouvatier et al., 2014). Finally, and maybe most importantly, variables of interest for the analysis of earnings management are different for banks and other financial institutions that are not engaged in sales-based businesses. As noted by Cohen et al. (2014), the focus of earnings management studies in the banking industry is on variables specific to this industry (e.g. loan loss provisions, realisation of gains or losses on securities).

Banking has provided a fertile ground for earnings management research since numerous studies have investigated this practice. Studies have primarily focused on loan loss provisions (e.g. Ahmed et al. (1999); Beaver and Engel (1996); Beck and Narayanamoorthy (2013); Bikker and Metzemakers (2005); Bouvatier et al. (2014); Bushman and Williams (2012); El Sood (2012); Fonseca and Gonzalez (2008); Laeven and Majnoni (2003); Pérez, Salas-Fumás, and Saurina (2008)).[6] Other studies have also explored security gains and losses (e.g. Agarwal, Chomsisengphet, Liu, and Rhee (2007); Beatty, Chamberlain, and Magliolo (1995); Beatty et al. (2002); Collins, Shackelford, and

[6] Loan loss provisions is a relatively large accrual that has a significant impact on earnings. The purpose of loan loss provisions is to adjust banks' loan loss reserves to reflect expected future losses. The recognition of expected loan losses occurs through the loan loss provision, classified as an expense account (Bikker & Metzemakers, 2005).

Wahlen (1995); Cornett et al. (2009)).[7]

These two elements have been labelled as discretionary accruals because they involve a significant degree of subjectivity (Bikker & Metzemakers, 2005; Cornett et al., 2009). In the presence of earnings management, these two elements are predicted to vary with nondiscretionary earnings (Shrieves & Dahl, 2003). Banks with relatively unfavourable nondiscretionary earnings are expected to underestimate loan loss provisions more than banks with more favourable figures in order to avoid reporting small losses. Similarly, banks with relatively unfavourable earnings are expected to realise more security gains or fewer security losses.

In the studies briefly mentioned, the presence of earnings management is typically assessed within a regression framework relating some earnings measure to loan loss provisions (or security gains and losses). In this study, we opt for the distributional approach, a relatively modern study design that, to our knowledge, has only been used by Shen and Chih (2005) for the banking industry. Using a sample consisting of 70,955 (bank-year) observations for the fiscal years 1993-1999 across 48 countries and 47,154 banks, the authors reported the presence of a kink around zero earnings that, similar to prior studies for the nonfinancial industry, was interpreted as evidence of earnings management. Unlike Dechow et al. (2003) for the nonfinancial industry, they did not consider the existence of a potential pre-managed earnings distribution. Similarly, they did not analyse earnings streams occurring between pre-managed and reported income to find the cause of the kink. These issues remain, to the best of our knowledge, unexplored for the banking industry.

Compared to prior results for the nonfinancial industry (e.g. Burgstahler and Dichev (1997), Dechow et al. (2003)), the shape of the distribution found by Shen and Chih (2005) as well as the kink differ. Studies in the nonfinancial industry have reported a bell-shaped distribution over the whole earnings spectrum with one irregularity around zero earnings. The distribution reported by Shen and Chih (2005) shows a half-normal distribution.[8] As observed by Shen and Chih (2005), earnings less than zero in general, and not only small losses, occur much less frequently than positive earnings. In addition, the frequency distribution shows a continuously decreasing

[7] Due to data availability, studies exploring security gains and losses are, to the best of our knowledge, limited to the U.S. and Japan. International studies that typically use data from Bankscope do not look at this issue because of insufficient data availability.

[8] We report the histogram displayed by Shen and Chih (2005) on Figure 4.3.

pattern on the left side of its peak. Shen and Chih (2005) underlined these patterns as important differences between the financial and the nonfinancial industry. Earnings management in banking seems therefore to be characterised by a lower frequency of firms with negative earnings, and not only by a lower frequency of small loss firms compared to small profit firms as it is the case in the nonfinancial industry.

[**Figure 4.3 about here**]

4.3. Data and methods

4.3.1. Data

We use data from Bankscope, a database maintained by Bureau Van Dijk which contains financial information on banks. Similar to related studies, we consider listed banks, thus ensuring a relatively high quality of data and enhancing comparability across countries (Laeven & Levine, 2007). Since listed banks are usually the largest, the sample that we consider also accounts for the majority of total assets. Our sample covers the 15-year period between 1999-2013. This time frame ensures the inclusion of periods with different business cycles and stock market conditions (e.g. Dot-com bubble, economic expansion of the early 2000s, financial crisis, Great Recession, sovereign debt crisis). Our sample is free from survivorship bias since we also consider banks that have been delisted at some point during the sample period. We eliminate banks classified as Islamic banks because the accounting information does not match with the rest of the sample (Laeven & Levine, 2007).

Many empirical studies focus on the discretionary portion of a manager's financial report, i.e. transactions for which managers are more likely to exercise financial judgement, and several focus on earnings streams that occur between cash flows from operations and reported net income (Healy & Wahlen, 1999). Due to the specificity of the banking industry and data availability, we focus on earnings streams that occur between Pre-impairment operating profit and Net income. We argue that, similar to cash flow from operations among nonfinancial firms, Pre-impairment operating profit can be considered as a measure of pre-managed earnings. First, as a measure of operating profit, it reflects a bank's revenue from its core activities. Second, it is largely unaffected by impairment charges that are known to be used for earnings management purposes in banking. And third, as displayed in Figure 4.4, Pre-impairment operating profit shows a smooth underlying distribution. It is therefore similar to the earnings distribution reported by Dechow et al. (2003) for nonfinancial firms and labelled as pre-managed earnings.

[Figure 4.4 about here]

Table 4.1 shows how Bankscope displays data from the income statement. While the income statement shows a certain degree of granularity, several positions are characterised by a high proportion of missing values. Exploring every single position would therefore result in the exclusion of a substantial number of observations, sometimes almost all of them. For this reason, we decided to concentrate on the positions marked in bold in Table 4.1. These positions are Pre-impairment operating profit, Operating profit, Pre-tax profit, and Net income.[9] Following Dechow et al. (2003), we scale earnings measures by beginning-of-the-year common equity. In the robustness section, we also scale earnings measures by beginning-of-the-year total assets.[10] We address extreme values, similar to Dechow et al. (2003) or Burgstahler and Dichev (1997), and winsorise accounting variables at the 1% and 99% level.

[Table 4.1 about here]

4.3.2. Methods

As noted by Healy and Wahlen (1999), central questions addressed in the empirical literature are about the positions of the income statement that are used to manage earnings as well as the magnitude of earnings management. To answer these questions, we employ the distributional approach and proceed as follows. First, we analyse the distributions of several earnings measures in order to assess the presence of a kink and the existence of a potential smooth pre-managed distribution. We then analyse several earnings streams occurring between pre-managed earnings and net income to assess which of these streams contribute to the kink, and ultimately whether earnings management is the cause of the kink.

[9]Sufficient data on Net income before profit transfers were available as well, but we decided not to focus on this position since it is largely identical to Net income. Thus, differences between Pre-tax profit and Net income comes from Tax expense and Profit/Loss from discontinued operations, but not from Profit transfers to parent companies.

[10]Several studies (e.g. Burgstahler and Dichev (1997); Fonseca and Gonzalez (2008)) use beginning-of-the-year figures as well to scale earnings measures in order avoid simultaneity bias.

Kink and smooth pre-managed earnings

To investigate the presence of a kink around zero earnings as well as the presence of a smooth pre-managed earnings distribution, we consider the distribution of various earnings measures. We conduct an initial inspection of the distributions by plotting the underlying histograms of Pre-impairment operating profit, Operating profit, Pre-tax profit, and Net income. In addition to displaying these histograms, we also show superimposed histograms in order to better highlight differences between distributions.

We then conduct the three statistical tests used by Shen and Chih (2005) to assess the presence and the extent of an irregularity around zero earnings. The null hypothesis of these various tests is that there is no discontinuity around zero earnings. To set intervals (or bin) width for the statistical tests, we use the method described by Wand (1995) in which bin width is defined as $2(\text{IQR})n^{-1/3}$, where IQR is the sample interquartile range of the variable and n is the number of available observations. This method was also used by Degeorge et al. (1999) in a study about earnings management.

The first statistic used by Shen and Chih (2005), EM1, comes from Burgstahler and Dichev (1997). EM1 is the difference between the actual and the expected number of observations in the interval immediately to the right of zero, such that

$$\text{EM1} = \frac{AQ_i - EQ_i}{SD_i}. \tag{4.1}$$

AQ_i and EQ_i are respectively the actual and the expected number of observations in interval i, the interval immediately right to zero. EQ_i is defined as the average of the number of observations in the two immediately adjacent intervals. SD_i is the estimated standard deviation of the difference between AQ_i and EQ_i.[11] Under the null hypothesis, these standardised differences will be

[11] $EQ_i = (AQ_{i-1} + AQ_{i+1})/2$; Since, according to Burgstahler and Dichev (1997, p. 103), the number of observations in an interval is a random variable which is approximately independent of the number in adjacent intervals, the variance of the difference between the observed and expected number of observations is approximately the sum of the variances of the components of the difference. Denoting the total number of observations as N and the probability that an observation will fall into interval i by p_i (proportion of the actual number of observations for interval i, AQ_i/N), the variance of the difference between the observed and expected number of observations for interval i is approximately $SD_i = [Np_i(1-p_i) + (1/4)N(p_{i-1} + p_{i+1})(1 - p_{i-1} - p_i + 1)]^{1/2}$.

distributed approximately normally with mean 0 and standard deviation 1 (Burgstahler & Dichev, 1997).

The second statistic, EM2, comes from Degeorge et al. (1999). EM2 considers a broader portion of the distribution, namely five intervals to the left of zero, and five intervals to the right of the first interval immediately right to zero. Formally,

$$\text{EM2} = \frac{\Delta p_i - MEAN(\Delta p_{-i})}{SD(\Delta p_{-i})}, \tag{4.2}$$

where p_i is the ratio of the actual number of observations for interval i to bank-years and $\Delta p_i = p_i - p_{i-1}$. $MEAN(\Delta p_{-i})$ is the average value of Δp, excluding p_i, i.e. $(\sum_{k=-5;k\neq 0}^{5} \Delta p_{i+k})/10$ and $SD(\Delta p_i)$ is the standard deviation of Δp, excluding Δp_i. k stands for intervals, while i stands for the interval immediately right to zero. EM2 is distributed as Student's t distribution under the null hypothesis (Degeorge et al., 1999; Shen & Chih, 2005).[12]

The third statistic, EM3, is inspired by Burgstahler and Dichev (1997) and Leuz, Nanda, and Wysocki (2003). It computes the ratio of the actual number of observations for interval i (small profits) to that of observations for the interval $i-1$ (small losses), or formally

$$\text{EM3} = AQ_i/AQ_{i-1}. \tag{4.3}$$

EM3 represents the ratio of the frequency of small profits to small losses. Unlike EM1 or EM2, it is not a statistic, but a simple ratio that cannot be used to formally assess the null hypothesis. A value for EM3 much greater than unity is interpreted as evidence that banks manage earnings, and a large value suggests a high degree of earnings management.

Earnings streams

In a second step, we analyse various earnings streams occurring between the different earnings positions considered. We construct stream variables by subtracting values of earnings positions

[12] As noted by Degeorge et al. (1999), the distribution of EM2 is likely to be well approximated by the Student's t-distribution under the null hypothesis if the distribution of Δp_i is approximately Gaussian. See Degeorge et al. (1999) for more details.

described earlier. First, we analyse the total earnings stream defined as the difference between Pre-impairment operating profit and Net income (PIOP−NI). We further decompose PIOP−NI into PIOP−OP (earnings stream between Pre-impairment operating profit and Operating profit), OP−PTP (earnings stream between Operating profit and Pre-tax profit) and PTP−NI (earnings stream between Pre-tax profit and Net income). The relation between the various levels and streams variables can be illustrated as follows:

$$\begin{aligned}
&\text{Net Income (NI)}\\
&+\text{PTP} - \text{NI}\\
&= \text{Pre-tax profit (PTP)}\\
&+\text{OP} - \text{PTP}\\
&= \text{Operating profit (OP)}\\
&+\text{PIOP} - \text{OP}\\
&= \text{Pre-impairment operating profit (PIOP)}
\end{aligned}$$

The decomposition of total earnings stream can be illustrated as follows:

$$\begin{aligned}
\text{PIOP} - \text{NI} = {} & \text{PIOP} - \text{OP}\\
& + \text{OP} - \text{PTP}\\
& + \text{PTP} - \text{NI}
\end{aligned}$$

Finally, the composition of each earnings stream, as shown in Table 4.1, can be illustrated as follows:

$$\text{PIOP-OP}\begin{cases} -\text{Loan Impairment Charge} \\ -\text{Securities and Other Credit Impairment Charges} \end{cases}$$

$$\text{OP-PTP}\begin{cases} +\text{Non-recurring Income} \\ -\text{Non-recurring Expense} \\ +\text{Other Non-operating Income and Expenses} \\ +\text{Equity-accounted Profit/ Loss - Non-operating} \\ +\text{Change in Fair Value of Own Debt} \end{cases}$$

$$\text{PTP-NI}\begin{cases} -\text{Tax expense} \\ -\text{Profit/Loss from Discontinued Operations} \\ +\text{Profit transfers to parent companies} \end{cases}$$

Earlier, we highlighted differences between the frequency distributions of financial and nonfinancial firms. Nonfinancial firms are characterised by a lower frequency of small loss firms compared to small profit firms while banks are characterised by a lower frequency of firms reporting losses in general relative to firms reporting profits. Given this important difference, it is unlikely that the kink in the distribution of banks comes exclusively from small profit firms and small loss firms managing earnings streams differently, as hypothesised by Dechow et al. (2003).[13] Thus, unlike Dechow et al. (2003), we do not focus our analysis on the earnings streams of these two earnings groups, but consider other portions of the distributions that are in our view more likely to cause the kink.

Our approach focuses on banks with small positive earnings versus banks with larger earnings. As can be observed from the superimposed histogram displayed in Figure 4.5, the number of banks located left to zero appears to be relatively constant for both Net income and Pre-impairment operating profit. In contrast, the number of observations located in the first intervals right to zero (approximately in the 15 first intervals right to zero) appears to be substantially higher in the Net income distribution. The number of observations beyond this threshold, reflecting banks

[13]Given the shape of the distribution prevailing in the nonfinancial industry, Dechow et al. (2003) hypothesised that small profit firms should have earnings streams boosting reported earnings more heavily relative to small loss firms if the kink is driven by earnings management. According to the authors, this would explain why firms move from reporting a small loss to reporting a small profit, i.e. by managing earnings up, ultimately resulting in a low proportion of firms in the small loss group and a high proportion of firms in the small profit group.

with relatively high earnings, is higher in the distribution of Pre-impairment operating profit. From this histogram, one can observe that the kink results from an asymmetrical shift to the left from the distribution of Pre-impairment operating profit. This shift is asymmetrical in the sense that it appears to affect mainly banks with positive earnings, while, at first glance, banks with negative earnings seem to remain largely unaffected. One could get the impression that the kink and the half-normal distribution both result from the accumulation of (1) banks with small positive pre-managed earnings staying in the small earnings area and (2) banks with higher pre-managed earnings being shifted into the small earnings area.

[**Figure 4.5 about here**]

In order to stay in the positive earnings area, banks with small pre-managed earnings seem more likely to manage earnings streams by understating them in absolute terms. In contrast, banks with higher pre-managed earnings can afford higher earnings streams, i.e. streams that reduce reported income more heavily, and therefore do not need to practice earnings management. As for banks with negative earnings, we refrain from making any prediction. If reporting positive earnings is the only motivation behind earnings management (i.e. under a simple loss avoidance story, see Dechow et al. (2003)), banks with negative pre-managed earnings are unlikely to manage earnings. If, on the other hand, the magnitude of negative earnings matters, they may manage earnings, similar to small earnings banks, in order to avoid reporting too heavy losses.

To empirically test this intuition that practising earnings management depends on the level of pre-managed earnings, we compare earnings streams from three different earnings groups. The first group consists of banks with negative pre-managed earnings (negative earnings banks), the second group consists of banks with relatively small positive earnings (small earnings banks), and the third group consists of banks with higher earnings (higher earnings banks). We define small earnings banks as those banks with pre-managed earnings located within the first 15 intervals right to zero based on the following arguments. The first 15 intervals right to zero correspond to the portion of the distribution in which there are more observations in the distribution of Net income compared to the distribution of Pre-impairment operating profit. This portion of earnings is also particularly important since most of the distributional changes happen in this interval. It also roughly corresponds to the portion of positive earnings left to the peak of the distribution of Pre-impairment operating profit (interval 17). In the robustness section, we consider alternative definitions for the earnings groups based on different interval numbers. We use a graphical approach and compute mean differences between earnings streams in the three earnings groups to formally assess the significance of the results.[14] Our ultimate goal is to assess what earnings streams, starting from a smooth pre-managed distribution, contribute to the apparition of the kink around zero in the distribution of Net income.

4.3.3. Descriptive statistics

Descriptive statistics of the various levels and streams variables are displayed in Table 4.2. Pre-impairment operating profit divided by common equity (PIOP) has the highest mean value, followed by Pre-tax profit (PTP), Operating profit (OP), and finally Net income (NI). Consequently, total earnings stream occurring between Pre-impairment operating profit and Net income (PIOP−NI) reflects an earnings reduction. Similarly, PIOP−OP and PTP−NI also reflect earnings reductions between the respective positions. As we have seen, these earnings streams are constituted mainly by impairment charges (on loans, securities, and other credits) and by tax expenses. OP−PTP reflects a slight earnings increase. Finally, Table 4.3 displays country-specific descriptive statistics to show the geographical composition of the sample. Similar to many international studies in the banking industry, the share of U.S. banks is not negligible. In the robustness section, we consider various geographical subsets to see whether geographical characteristics may drive the results obtained in the whole sample.

[Table 4.2 about here]

[Table 4.3 about here]

[14] In addition to Dechow et al. (2003), Beatty et al. (2002) also used the same formal test to compare measures of earnings management across groups of banks characterised by different attributes, notably ownership structure and inclusion into specific earnings groups.

Table 4.4 displays correlation coefficients between the variables analysed. As expected, the various earnings measures are significantly and positively correlated to another. For example, PIOP is positively and significantly correlated with OP (0.87), PTP (0.60), and NI (0.45). The further down the income statement one goes, the smaller the coefficients are. These earnings measures further down the income statement (OP, PTP, OP) therefore increasingly distance themselves from PIOP, a progressive discrepancy caused by earnings streams happening in-between.

[**Table 4.4 about here**]

The correlations between PIOP and the various earnings streams are significantly positive. The correlations between PIOP and PIOP−NI, PIOP−OP, and PTP−NI are particularly high. This reflects the fact that banks with higher Pre-impairment operating profit also have higher earnings streams, i.e. earnings streams that reduce reported profit more heavily than earnings streams of banks with smaller Pre-impairment operating profit. Finally, the correlation between OP and PTP−NI is also highly significant and quite large, suggesting that banks with higher Operating profit also have higher tax expenses. The correlations briefly discussed might be a first hint suggesting that PIOP−OP and PTP−NI are responsible for the apparition of the kink in the earnings distribution.

4.4. Earnings distributions' analysis

As noted earlier, earnings management to avoid losses is likely to be reflected in cross-sectional distributions of earnings in the form of a threshold-driven discontinuity in the earnings distribution, typically a kink around zero earnings. Thus, if earnings management is prevalent in the banking industry, we expect to find evidence suggesting the existence of this irregularity in the form of a kink.

4.4.1. Graphical evidence

On Figure 4.6, we display histograms of the various earnings measures considered. For the inspection of the graphs, we set the bin width at 0.01 for every earnings measure to guarantee graphical homogeneity and to facilitate the comparison between distributions. The first histogram (Pre-impairment operating profit) shows a single-peaked, bell-shaped distribution. At first glance, this distribution does not show any irregularity around zero earnings that may suggest the presence of earnings management.

[**Figure 4.6 about here**]

The second histogram (Operating profit) is different in the sense that it does not show a distribution as smooth and regular as the first one. We can observe the formation of a kink around zero earnings suggesting that the frequency of small profit banks to small loss banks is abnormally high. The same conclusion applies to the third graph (Pre-tax profit). It displays a similar histogram, and no obvious departure from the previous position can be observed. On the fourth histogram (Net income), the distribution further departs from the initial smooth distribution and the kink around zero appears to be reinforced. This distribution comes relatively close to the "half-normal" distribution reported by Shen and Chih (2005).

In order to further highlight the evolution of earnings between Pre-impairment operating profit and Net income, superimposed histograms are displayed in Figure 4.7. The first graph shows the distributions of Pre-impairment operating profit and Net income, i.e. the total evolution of earnings between the initial smooth distribution and the final distribution of reported earnings. The overall picture suggests that the distribution of Pre-impairment operating profit is asymmetrically shifted to the left. As a consequence, more banks end up reporting relatively small earnings. The shift appears to be asymmetrical since it seems to affect primarily banks with positive earnings rather than applying symmetrically to the whole distribution.

[**Figure 4.7 about here**]

In the three following graphs, we superimpose earnings of subsequent positions down the income statement in order to decompose the partial shift to the left. The second graph shows a first pronounced shift between Pre-impairment operating profit and Operating profit and the apparition of the kink. As a result, more banks report smaller earnings and fewer report larger earnings. Finally, the peak of the two distributions seems to be at relatively similar height. The third graph reinforces the impression that Operating profit and Pre-tax profit do not substantially differ from another. The fourth graph shows that a second substantial shift to the left takes place between Pre-tax profit and Net income. Again, fewer banks end up reporting large earnings and more banks end up reporting small earnings. In addition, the peak of the distribution is now higher. Again, the negative area does not seem to be substantially affected.

Looking at (superimposed) histograms reinforces our initial idea based on descriptive statistics and on the correlation matrix. Earnings streams occurring between Pre-impairment operating profit and Operating profit, and between Pre-tax profit and Net income appear to be the main drivers behind the apparition of the kink and its subsequent reinforcement. The analysis of superimposed histograms further shows that these earnings streams result in a greater number of banks reporting small earnings, and a smaller number of banks reporting larger earnings. The area of the distribution located to the left of zero (negative earnings) appears to be largely unaffected.

4.4.2. Statistical tests

After looking at graphical evidence suggesting the progressive apparition of a kink in the distribution of successive earnings positions, we proceed with the three statistical tests described in Section

4.3 to formally assess the presence of an irregularity around zero earnings. For the graphical analysis, we have uniformly set histogram bin width at 0.01 in order to facilitate the comparison of the various distributions. For this statistical test, we use the method described in Section 4.3 that results in more precise estimates. For each earnings variable, results of the three statistical tests are reported in Table 4.5. The null hypothesis of these various tests is that there is no discontinuity around zero earnings.

[**Table 4.5 about here**]

For Pre-impairment operating profit, we fail to reject the null hypothesis of no irregularity with both EM1 and EM2. In addition, EM3 is not substantially larger than one. Thus, Pre-impairment operating profit does not show any sign of an irregularity around zero earnings. For all other earnings measures, however, the statistical tests indicate the presence of a kink around zero earnings. Both EM1 and EM2 are statistically significant at the highest significance level. In addition, EM3 is substantially greater than unity. The various statistics further indicate a bigger irregularity around zero earnings in the distribution of Net income. Compared to Operating profit and Pre-tax profit, this variable has the highest values for the three earnings management statistics.

Results from these statistical tests reinforce the idea that, starting from a smooth, bell-shaped distribution (Pre-impairment operating profit), earnings measures further down the income statement show the progressive apparition of a discontinuity around zero earnings. This irregularity culminates with a pronounced kink around zero in the distribution of Net income. This evolution is consistent with earnings streams occurring between Pre-impairment operating profit and Net income causing the kink. It is likely that earnings streams play a major role between Pre-impairment operating profit and Operating profit (apparition of the kink) and between Pre-tax profit and Net income (reinforcement of the kink).

4.5. Earnings streams' analysis

4.5.1. Graphical evidence and statistical tests

In this section, we analyse earnings streams of different earnings groups. Our main hypothesis is that banks manage earnings streams depending on their level of pre-managed earnings. More precisely, we expect to find higher earnings streams among higher earnings banks (located beyond earnings interval 15) relative to small earnings banks (interval 1 to 15). Under a simple loss avoidance story, higher earnings banks can afford a larger reduction of their pre-managed earnings relative to small earnings banks.

As a first cut to relate Pre-impairment operating profit to subsequent earnings streams, Figure 4.8 plots bank-year observations for the different earnings streams as a function of Pre-impairment operating profit. From the upper-left panel (PIOP−NI), one can observe a positive relationship between these two variables. This relationship prevails in the positive portion of the x axis, i.e. for banks with positive pre-managed earnings. It reflects the fact that banks with higher pre-managed earnings also have higher total earnings stream. The same positive relationship can also be observed between pre-managed earnings and PTP−NI (lower-right panel). A positive relationship, though less clear-cut, between pre-managed earnings and PIOP−OP also appears to be reflected on the upper-right panel of Figure 4.8.

[**Figure 4.8 about here**]

Due to the large number of observations included in this study, the various plots displayed on Figure 4.8 may appear confusing for the graphical analysis. To address this issue, we use smooth nonparametric regressions based on locally-weighted polynomial regression (LOWESS). Given the concentration of observations showed in the middle area of the graphs of Figure 4.8, there is concern that extreme observations may strongly affect estimation results of a least square regression. We plot the regression line for each earnings stream on Figure 4.9.

[**Figure 4.9 about here**]

The four plots of this figure confirm our prior impressions. One can recognise a positive association between total earnings streams PIOP−NI and Pre-impairment operating profit (upper-left panel) reflecting the fact that small earnings banks have lower earnings streams further down the income statement compared to higher earnings banks. The line seems to flatten for banks with the smallest positive earnings. The decomposition of total earnings streams shows that small earnings banks have lower PIOP−OP (upper-right panel) than higher earnings banks, with again a flattening of the line observed for the smallest positive earnings banks. For PTP−NI (lower-right panel), the plot also shows a positive relationship between this stream variable and pre-managed earnings, but without flattening of the line for the smallest positive earnings banks. Finally, the lower-left panel (OP−PTP) shows a flat line and no obvious association.

In Figure 4.10, we display the four earnings distributions investigated in this study. Each distribution is broken down by earnings groups. Negative earnings banks are displayed in white, small earnings banks in lightgrey, and higher earnings banks in darkgrey. With this way of breaking down earnings, we can see where banks, grouped according to their level of pre-managed earnings, end up in each earnings distribution further down the income statement. The upper panel shows the smooth, pre-managed earnings distribution of Pre-impairment operating profit. Since earnings groups are formed based on this distribution, there is a clear-cut horizontal separation between the three earnings groups. This is not the case on the next graphs, in which several banks-observations are shifted compared to their initial position, mostly to the left.

[**Figure 4.10 about here**]

Figure 4.11 displays the distribution of Net income for each earnings group on a separate plot. As can be seen, negative earnings banks (upper panel) do not appear to play a major role in the apparition of the kink. In contrast, one can observe a kink around zero earnings for small earnings banks (middle panel). As for higher earnings banks (lower panel), there is no obvious kink around zero earnings. This graphical evidence indicates that the kink is likely to come from the small earnings group.

[**Figure 4.11 about here**]

We show on Figures 4.12 to 4.15 histograms of the various earnings streams investigated. For each variable, we show the distribution of each earnings group separately. In addition, we compute mean difference tests in order to compare the earnings streams of the different earnings groups in a more formal way. Results of the tests are shown in Table 4.6.

[**Figure 4.12 about here**]

[**Figure 4.13 about here**]

[**Figure 4.14 about here**]

[**Figure 4.15 about here**]

[**Table 4.6 about here**]

We start the analysis with total earnings stream PIOP−NI. As can be seen from Figure 4.12, the peak of the distribution of small earnings banks is closer to zero compared to the peak of the distribution of higher earnings banks. In addition, the tail on the right side of the distribution of higher earnings banks is fatter compared to the tail on the right side of the distribution of small earnings groups. This pattern is reflected by a significantly lower earnings stream for small earnings banks compared to higher earnings banks in the mean difference test (Panel A of Table 4.6). The interpretation is that banks with higher pre-managed earnings have larger total earnings streams, i.e. earnings streams that reduce reported profits more heavily, compared to banks with smaller pre-managed earnings, and the difference is statistically significant.

Next we turn to PIOP−OP. As discussed earlier, this earnings stream mostly consists of impairment charges on loans, securities, and other credits. Both small earnings banks and higher earnings banks have their peak at the same interval, the first interval right to zero (see Figure 4.13). Again, the tail on the right side of the distribution of higher earnings banks is fatter than the tail on the right side of the distribution of small earnings banks. Mean difference tests for this stream variable (Panel B of Table 4.6) show that higher earnings banks have a higher earnings stream compared to small earnings banks, and the difference is again highly significant.

Confirming the intuition developed so far, the next earnings stream, OP−PTP does not appear to play a major role in explaining the kink in the distribution of reported earnings. The various plots of Figure 4.14 show that this stream variable is mostly centred around zero, especially in the distributions of small earnings banks and higher earnings banks. That is, this earnings stream is unlikely to be responsible for the apparition of the kink. This is confirmed by the mean differences tests of Table 4.6 (Panel C). Average mean of small earnings banks and higher earnings banks are very close to zero, and none of the mean difference is statistically significant.

The last earnings stream variable is PTP−NI. This earnings stream mainly reflects tax expenses. Similar to PIOP−NI, the peak of the distribution of small earnings banks is closer to zero compared to the peak of the distribution of higher earnings banks (Figure 4.15). In addition, the tail on the right side of the distribution of higher earnings banks is fatter than the tail of the right side of the distribution of small earnings banks. All three mean difference tests are statistically significant at the highest level (Panel D of Table 4.6). This earnings stream is higher among higher earnings banks than it is among smaller earnings banks. It is in turn higher among smaller earnings banks than it is among negative earnings banks. This is very likely to reflect the fact that tax expenses are largely a positive function of earnings. Finally, the three earnings groups show a surge of observations in the first interval right to zero. This might be caused by the report of a tax relief following negative earnings in past periods and resulting in no tax expense in the current period (see also Section 4.5.2).

Finally, if we decompose total earnings stream for each earnings group, we can see that the larger earnings stream of smaller earnings banks is PIOP−OP (0.0534 of 0.0632). OP−PTP is negligible (−0.0016), and PTP−NI (0.0114) is fairly small in comparison. The composition of total earnings stream is slightly different for higher earnings banks. PIOP−OP is again the largest portion (0.1410 of 0.2237), and OP−PTP is again negligible (0.0010). PTP−NI, however, plays a bigger role (0.0816).

4.5.2. Synthesis

The two questions we seek to answer in this paper are (1) which specific earnings streams are responsible for the kink, and (2) is earnings management the driving force behind this irregularity. The evidence gathered in this paper shows that, depending on the level of pre-managed earnings, differences relating to impairment charges and tax expenses contribute to the formation and the reinforcement of the kink. The banking literature has widely documented the use of impairment charges for earnings management purposes. This earnings stream involves a significant degree of subjectivity that allows banks to use them for earnings management purposes. It is therefore likely that earnings management is, at least partially, behind the apparition of the kink.

Tax expenses, however, are a positive function of earnings. Banks with higher earnings have higher tax expenses compared to banks reporting smaller earnings. In this case, earnings management is not expected to play a major role. Thus, we argue that a portion of the kink in the distribution of reported earnings should not be attributed to earnings management. In order to better explain the kinking effect of taxation, we show the following model calculation.

We define Net income NI as Pre-tax profit minus tax expenses such as

$$\mathrm{NI} = \mathrm{PTP} \cdot (1 - s), \tag{4.4}$$

where s is the tax rate. In this example, we fix the tax rate at 20% of Pre-tax profit. We consider two banks that, for simplicity purposes, hold the same level of common equity. If Bank 1 has PTP of 1000 monetary units, it will have tax expenses of 200 and NI of 800. If Bank 2 has PTP of 100, it will have tax expenses of 20 and NI of 80. If we take a distributional approach, the shift of Bank 1 caused by tax expenses is 200 while the shift of Bank 2 is only 20. Thus, Bank 1 is disproportionately shifted to the left compared to Bank 2. This is for banks reporting positive earnings.

In case of negative PTP, in the U.S., the country that accounts for the highest number of banks in our sample, as well as in other countries (e.g. France) a bank, or another firm, can apply a tax relief. It can apply the loss to its past tax payments and receives a tax credit, or it can apply the loss to future income tax payments, reducing the need to make payments in future periods. The terms of the tax relief and how it can be applied vary by jurisdiction. Usually, loss applying to past tax payments are limited to the past few years (one to three years) and capped to a certain amount of money. In contrast, loss applied to future tax payments can be forwarded much more to the future (seven to 10 years) and are not capped. While each case is different, loss applied to future tax payments appear, on average, more likely. In addition, this difference in treatment of losses is unlikely to affect significantly our predictions regarding the kinking effect of taxation since banks reporting negative PTP are quite rare.

To illustrate our prediction regarding the kinking effect of taxation, we draw a random sample of 30,000 observations approximating a normal distribution with mean at 0.125 and standard deviation of 0.1 so that this random sample approximately fits (x and y range) with the sample of banks used in this study. This random distribution is used as a proxy for PTP. We multiply all observations with positive PTP of the random sample by 0.8% in order to simulate the effect of a tax rate of 20%. For the reason explained earlier, the observations with negative earnings are left unchanged. We display the result of this simulation in Figure 4.16 using superimposed histograms for these two earnings distributions.

[**Figure 4.16 about here**]

As can be seen, the result of this simulation fits quite well with the empirical data used in this study. Compared with the histogram of PTP, the histogram of NI shows less observations with high positive earnings and more observations with small positive earnings. Due to our assumption about negative earnings banks, the whole area left to zero earnings is identical for both earnings measures.

4.6. Robustness tests

We conduct several robustness tests of our results, both for the different earnings management statistics and for the mean difference tests of earnings streams among earnings groups. In these robustness tests, we consider sample splits according to geographical criteria, a different scaling of earnings, and the possibility that banks' main activities can have an influence on the results. We also consider alternative measures of intervals for both statistical tests. Overall, these robustness tests largely confirm our main results.

Geographic samples

So far, we have analysed the whole sample of international banks that covers developed as well as developing countries. As underlined by Elsas et al. (2010), banks in these different groups can be very heterogeneous with regard to regulation, ownership or market structures. This heterogeneity can have implication in terms of incentives and opportunity to conduct earnings management.

To account for the heterogeneity in economic development, we conduct a first robustness check by splitting the overall sample into OECD and non-OECD countries. Among both groups, results of the earnings management statistic tests confirm the presence of a smooth pre-managed distribution around zero earnings (Pre-impairment operating profit), as well as the presence of a discontinuity in distributions of earnings further down the income statement. Regarding earnings streams (Tables 4.8 and 4.9), mean difference tests confirm that higher earnings banks have higher total earnings streams PIOP−NI, impairment charges PIOP−OP, and tax expenses PTP−NI relative to smaller earnings banks. Mean differences are statistically significant at the highest confidence level.

[Table 4.7 about here]

[Table 4.8 about here]

[Table 4.9 about here]

We further look at results for samples of US and non-US banks. US banks traditionally make up a substantial share of banks in international studies. In this study, 11,069 of the 27,585 observations included in the final sample come from U.S. banks. Considering separate subsets allows us to check whether results are driven by characteristics of U.S. banks or whether they apply to the rest of the sample as well. Results for the earnings management statistics are displayed in Table 4.7 (Panels C and D) and mean difference tests of earnings streams in Table 4.11. Overall, the relative sample concentration on US banks does not appear to drive the significance of the results found in the paper.

[Table 4.10 about here]

[Table 4.11 about here]

Scaling effect

In the paper, we scaled the various earnings measures by common equity. For robustness purposes, we recalculate the primary results after scaling earnings measures by total assets. We display results for the earnings management statistics in Table 4.7 (Panel E) and for the mean difference tests of earnings streams in Table 4.12. These results are largely in line with those found in the paper.

[Table 4.12 about here]

Type of banks

Burgstahler and Dichev (1997) argued that certain firm-level characteristics can make earnings management an easier practice. A bank's main activity could be a characteristic that influences the degree of earnings management. Since the literature primarily emphasises the role of loan loss provisions, commercial banks focusing on lending could be more prone to earnings management practices than investment banks relying more heavily on nonlending activities. Results gained earlier could therefore be driven by banks with these characteristics. To investigate this possibility, we exclude specialised institutions from the sample.

Following Laeven and Levine (2007), we define specialised banks as those banks with net interest income below 10% of total income and above 90% of total income. Alternatively, Laeven and Levine (2007) also define specialised banks as those banks with net loans below 10% and above 90% of total earnings assets. As can be seen from Panels F and G of Table 4.7 for earnings management statistics and from Tables 4.13 and 4.14 for earnings streams, excluding specialised banks from the sample does not substantially influence the results. Our main findings are therefore not driven by characteristics of specialised institutions.

[**Table 4.13 about here**]

[**Table 4.14 about here**]

Alternative measures

Finally, we consider alternative measures for the various statistical tests conducted in the paper. For earnings management statistics, we alter the number of intervals considered to give more robustness to the results. We calculate EM1 as the difference between the actual and expected number of observations in the two intervals immediately right to zero. We compute the expected number of observations as the average of observations in the two intervals directly right and left to these two intervals. To compute EM2, we also consider a broader portion of the distribution. Instead of considering five intervals to the left of zero and five intervals to the right of the first positive interval, we consider 10 intervals to the left of zero and ten intervals to the right of the first positive interval. For EM3, we consider the two first intervals to the left of zero and the two first intervals to the right of zero instead of the first interval to the left of zero and the first interval to the right of zero. We find results similar to those reported earlier.

As for earnings streams, we defined small earnings banks as those banks with pre-managed earnings within the first 15 intervals to the left of zero. Similarly, we labelled as higher earnings banks all banks with pre-managed earnings located beyond the fifteenth interval. As robustness check, we define as small earnings banks those banks that are within the first 20 intervals (Table 4.15) or 10 intervals (Table 4.16) to the right of zero. Again, we found results close to those reported in the paper.

[**Table 4.15 about here**]

[**Table 4.16 about here**]

4.7. Conclusion

This paper analyses earnings management in banking and applies a distributional approach for a sample of international banks including 27,585 cross-sectional observations between 1999 and 2013. Banks being usually excluded from empirical earnings management studies, several thematics relating to this topic remain unexplored in the banking industry. Among other unexplored issues, the existence of a smooth pre-managed earnings distribution and whether earnings management does explain the kink in the distribution of reported earnings have, to our knowledge, never been addressed in the banking industry.

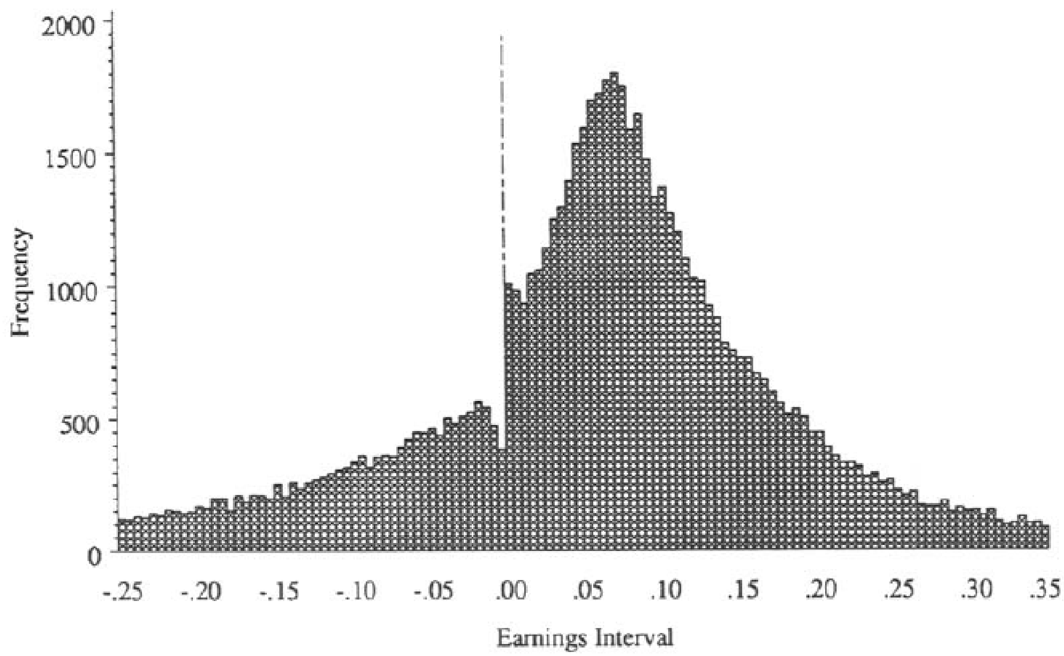
Evidence from graphical analyses and from statistical tests shows the presence of a smooth pre-managed earnings distribution (Pre-impairment operating profit), thus confirming previous findings from Dechow et al. (2003) for the nonfinancial industry. Evidence further shows the progressive apparition of a kink around zero earnings in earnings measures further down the income statement. The kink first appears in the distribution of Operating profit, and is further reinforced in the distribution of Net income. In order to investigate whether earnings management is behind the kink, we investigate earnings streams occurring between Pre-impairment operating profit and Net income.

Our results show that the apparition and reinforcement of the kink come from an asymmetric shift to the left affecting mostly banks with positive earnings. Between Pre-impairment operating profit and Net income, banks with relatively high pre-managed earnings are decisively shifted to the left, while banks with relatively small earnings are only moderately shifted to the left. This shift reflects higher total earnings stream among banks with higher pre-managed earnings, i.e. earnings streams that reduce more heavily reported earnings. This result is compatible with a loss avoidance story predicting that firms manage earnings in order to report profits, even small ones. Compared to banks with modest pre-managed earnings, banks with higher pre-managed earnings can afford higher hits to their earnings. Banks with smaller pre-managed earnings are therefore more likely to manage, i.e. understate, these earnings streams in order to avoid reporting losses.

We further decompose total earnings streams to investigate which specific earnings stream has an impact on the apparition and development of the kink. We find that banks with higher pre-managed earnings have on average (1) higher impairment charges on loans, securities, and other credits as well as (2) higher tax expenses relative to smaller earnings banks. The use of impairment charges, explained by the high degree of subjectivity associated with these expenses, for earnings management purposes is well-known and has been well-documented in the literature. However, since tax expenses are a positive function of earnings, earnings management does not seem to be the main driver behind the kinking effect of taxation. Therefore, the kink appears to be only partially caused by earnings management.

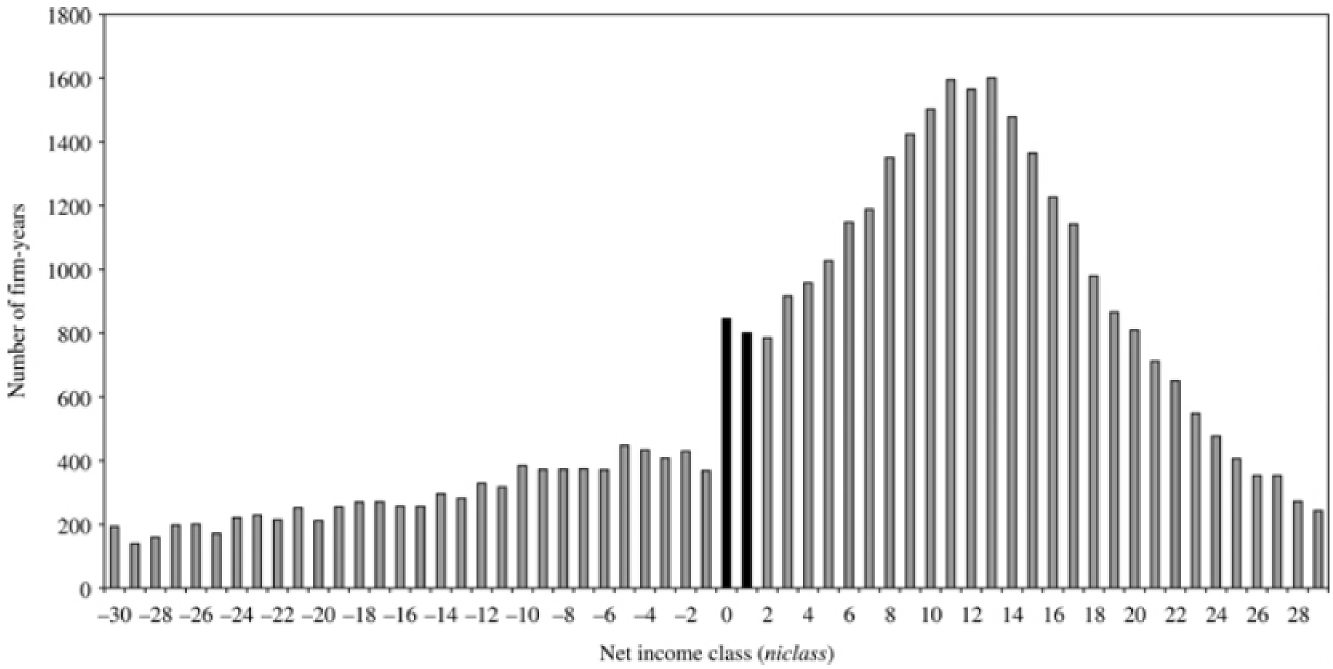
Several studies of the empirical literature have attributed the presence of a kink around zero earnings to earnings management without further investigation of the cause of the kink. The magnitude of the kink is further used to gauge the degree of earnings management in several studies. Our findings show that this approach is not unproblematic since factors other than earnings management, in our case tax expenses, also have a kinking effect. Thus, interpreting the presence of a kink around zero earnings as evidence of earnings management without further investigation bears the risk of drawing wrong conclusions.

Figure 4.1: Distribution of reported earnings taken from Burgstahler and Dichev (1997, Figure 3, p. 109)



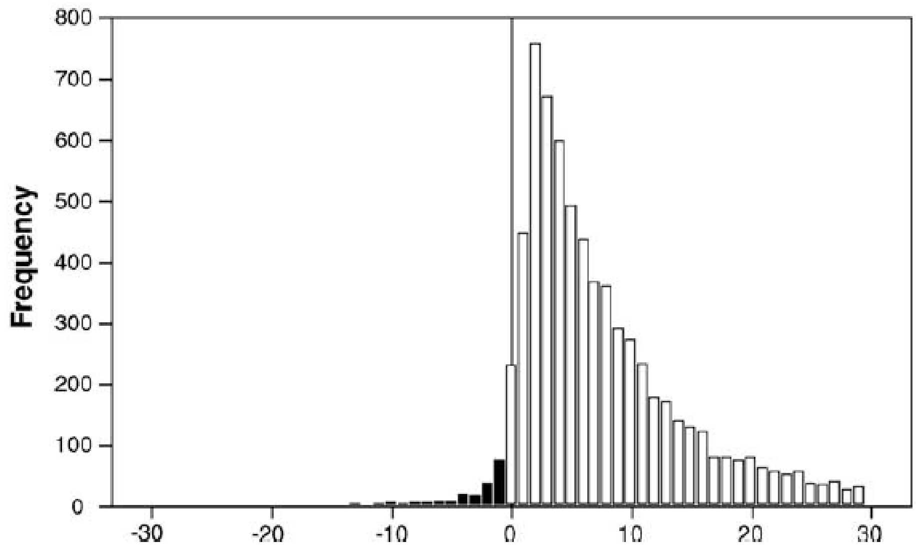
The figure shows the distribution of annual net income scaled by beginning of the year market value. The distribution intervals widths are 0.005 and the location of zero on the horizontal axis is marked by the dashed line. The sample includes all available observations on the annual industrial and research Compustat databases for the year 1976-1994 which meet minimal data requirements of the study of Burgstahler and Dichev (1997). Banks, financial institutions, and firms in regulated industries (e.g. utilities) are deleted. The final sample includes 64,466 observations.

Figure 4.2: Distribution of reported earnings taken from Dechow et al. (2003, Figure 5, p. 373)



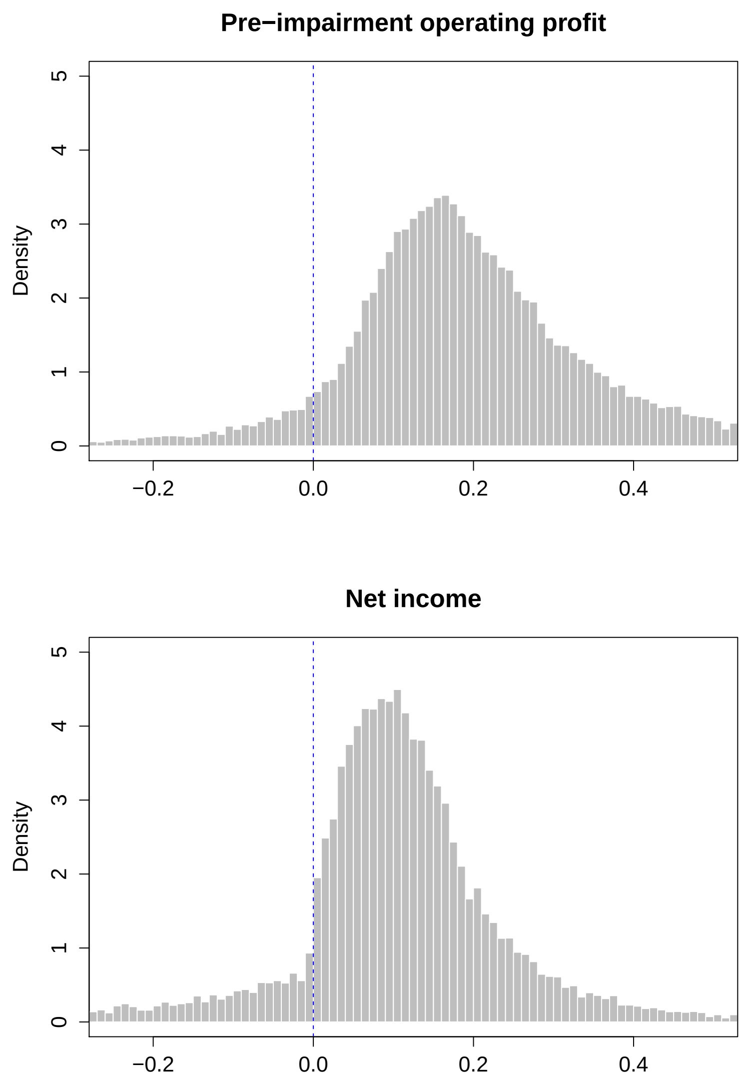
The figure shows the distribution of net income scaled by market value. The distribution intervals widths are 0.005. The sample includes all firm-years from 1988-2000 on Compustat that have the required financial statement information of the study of Dechow et al. (2003). The final sample consists of 47,847 firm-years.

Figure 4.3: Distribution of reported earnings taken from Shen and Chih (2005, Figure 1, Panel B, p. 2677)



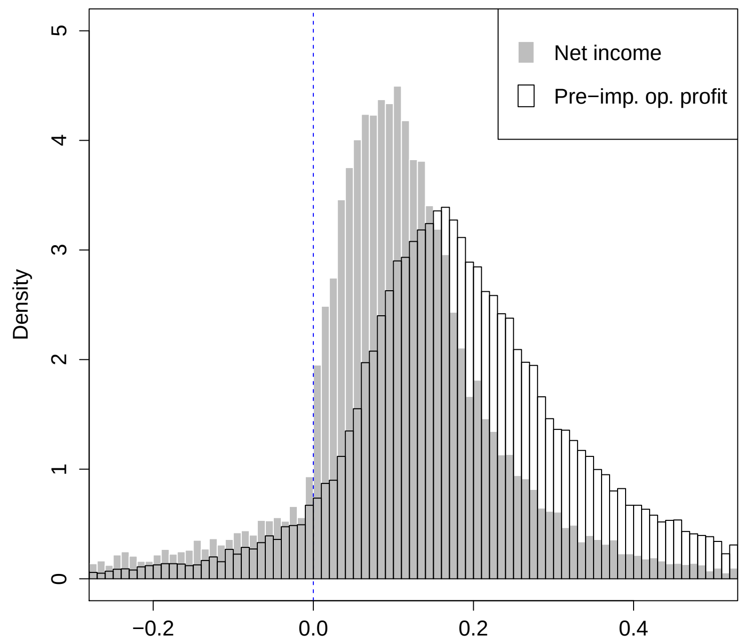
The figure shows the distribution of annual net income scaled by year-end common equity for U.S. banks for the period 1993 to 1999. The data are obtained from the Bankscope database. The sample consists of 7,461 observations.

Figure 4.4: Histograms of pre-managed and reported earnings



The figure shows histograms of various earnings measures for a sample of international banks between 1999-2013. All variables are scaled by beginning-of-the-year common equity. Bin width is set at 0.01 for all histograms. The location of zero earnings is marked by the dashed line.

Figure 4.5: Superimposed histograms of pre-managed and reported earnings



The figure shows superimposed histograms of various earnings measures for a sample of international banks between 1999-2013. All variables are scaled by beginning-of-the-year common equity. Bin width is set at 0.01 for all histograms. The location of zero earnings is marked by the dashed line.

Table 4.1: Bankscope income statement (Universal format)

10040 Gross Interest and Dividend Income	
	10010 Interest Income on Loans
	+10020 Other Interest Income
	+10030 Dividend Income
10070 Total Interest Expense	
	10050 Interest Expense on Customer Deposits
	+10060 Other Interest Expense
10080 Net Interest Income	
	10040 Gross Interest and Dividend Income
	−10070 Total Interest Expense
10140 Total Non-Interest Operating Income	
	10090 Net Gains on Trading and Derivatives
	+10100 Net Gains on Other Securities
	+10105 Net Gains on Assets at FV through Income Statement
	+10110 Net Insurance Income
	+10120 Net Fees and Commissions
	+10130 Other Operating Income
10170 Total Non-Interest Expenses	
	10150 Personnel Expenses
	+10160 Other Operating Expenses
10190 Pre-Impairment Operating Profit (PIOP)	
	10080 Net Interest Income
	+10140 Total Non-Interest Operating Income
	−10170 Total Non-Interest Expenses
	+10180 Equity-accounted Profit/ Loss - Operating
10220 Operating Profit (OP)	
	10190 Pre-Impairment Operating Profit
	−10200 Loan Impairment Charge
	−10210 Securities and Other Credit Impairment Charges
10270 Pre-tax Profit (PTP)	
	10220 Operating Profit
	+10240 Non-recurring Income
	−10250 Non-recurring Expense
	+10260 Other Non-operating Income and Expenses
	+10230 Equity-accounted Profit/ Loss - Non-operating
	+10255 Change in Fair Value of Own Debt
10283 Net Income before Profit Transfers	
	10270 Pre-tax Profit
	−10280 Tax expense
	+10282 Profit/Loss from Discontinued Operations
10285 Net Income (NI)	
	10283 Net Income before Profit Transfers
	−10284 Profit transfers to parent companies
10340 Fitch Comprehensive Income	
	10285 Net Income
	+10310 Change in Value of AFS Investments
	+10315 Revaluation of Fixed Assets
	+10320 Currency Translation Differences
	+10330 Remaining OCI Gains/Losses

Table 4.2: Descriptive statistics

	Obs.	Mean	Median	S.D.	Min.	Max.
PIOP	27,585	0.269	0.184	6.047	−536.438	516.879
OP	27,585	0.185	0.135	4.428	−169.414	506.091
PTP	27,585	0.210	0.137	4.953	−169.414	506.091
NI	27,585	0.168	0.102	4.505	−165.179	400.394
PIOP−NI	27,585	0.101	0.082	5.706	−663.840	138.620
PIOP−OP	27,585	0.084	0.034	3.092	−367.024	136.972
OP−PTP	27,585	−0.025	0.000	3.147	−468.234	58.667
PTP−NI	27,585	0.042	0.031	1.362	−80.857	105.697

The table provides descriptive statistics for the levels and streams variables used in this study. The sample covers international banks between 1999-2013. Variables are winsorised at the 1% and 99% levels to mitigate the impact of outliers. PIOP is Pre-impairment operating profit, OP is Operating profit, PTP is Pre-tax profit, NI is Net income, PIOP−NI is Earnings stream between PIOP and NI, PIOP−OP is Earnings stream between PIOP and OP, OP−PTP is Earnings stream between OP and PTP, PTP−NI is Earnings stream between PTP and NI. All variables are scaled by beginning-of-the-year common equity.

Table 4.3: Country-specific descriptive statistics

	Obs.	Assets	Equity	PIOP	OP	PTP	NI
Argentina	99	6,055	654	0.319	0.202	0.183	0.115
Armenia	16	129	23	0.220	0.197	0.197	0.163
Australia	106	187,641	10,856	0.228	0.186	0.212	0.184
Austria	150	62,086	3,773	0.207	0.104	0.113	0.084
Bahrain	143	5,930	659	0.145	0.089	0.102	0.100
Bangladesh	44	1,837	148	0.441	0.308	0.308	0.159
Barbados	26	5,304	686	0.149	0.111	0.153	0.131
Belgium	59	191,330	11,618	0.192	0.157	0.139	0.098
Belize	7	931	273	0.143	0.068	0.078	0.078
Benin	13	697	54	0.549	0.361	0.335	0.254
Bermuda	137	6,875	1,364	0.166	0.149	0.169	0.150
Bolivia	20	939	79	0.233	0.102	0.095	0.075
Bosnia-Herz.	82	374	41	0.227	0.089	0.033	0.031
Botswana	48	1,027	119	0.656	0.559	0.568	0.440
Brazil	312	29,410	2,613	0.340	0.040	0.021	0.064
Bulgaria	60	1,311	129	0.235	0.154	0.157	0.135
Burkina Faso	14	308	22	0.665	0.445	0.398	0.265
Canada	54	195,401	9,523	0.166	0.140	0.137	0.104
Cape Verde	9	670	41	0.279	0.179	0.179	0.147
Cayman Islands	14	1,015	86	0.137	0.123	0.122	0.122
Chile	56	20,579	1,471	0.392	0.281	0.275	0.233
China	133	556,219	33,255	0.412	0.334	0.334	0.216
Colombia	124	12,292	981	10.928	7.960	8.581	6.014
Costa Rica	58	600	65	0.258	0.192	0.197	0.176
Ivory Coast	40	679	76	0.308	0.185	0.172	0.134
Croatia	263	2,151	256	0.134	0.062	0.063	0.045
Cyprus	60	15,939	1,002	0.345	0.118	0.120	0.175
Czech Rep.	34	25,987	2,089	0.305	0.248	0.260	0.200
Denmark	463	13,981	603	0.202	0.104	0.104	0.074
Ecuador	70	1,782	132	0.248	0.083	0.157	0.121
Egypt	270	2,540	264	0.861	0.668	0.457	0.437
El Salvador	85	1,604	151	0.326	0.156	0.190	0.154
Estonia	22	11,281	1,139	0.268	0.197	0.199	0.196
Finland	59	17,605	1,920	0.200	0.184	0.168	0.138
France	508	131,834	4,557	0.194	0.163	0.180	0.133
Gambia	14	89	9	0.788	0.704	0.704	0.461
Georgia	34	720	115	0.297	0.021	0.031	0.014
Germany	448	131,766	3,718	0.140	0.072	0.062	0.029
Ghana	45	804	98	0.589	0.487	0.489	0.351
Greece	106	41,472	2,169	0.068	−0.072	−0.360	−0.425

The table provides country-specific information about the number of observations and average values of different variables for the sample of international banks between 1999-2013 used in this study. Obs. is the number of bank-year observations, Assets is total book assets, Equity is total book equity, PIOP is Pre-impairment operating profit scaled by beginning-of-the-year common equity, OP is Operating profit scaled by beginning-of-the-year common equity, PTP is Pre-tax profit scaled by beginning-of-the-year common equity, NI is Net income scaled by beginning-of-the-year common equity.

Table 4.3: Country-specific descriptive statistics (continued)

	Obs.	Assets	Equity	PIOP	OP	PTP	NI
Hong Kong	143	31,333	3,280	0.152	0.122	0.141	0.125
Hungary	36	13,929	1,503	14.700	14.303	14.303	11.322
Iceland	26	14,944	−1,455	0.236	0.196	0.196	0.167
India	676	19,595	1,297	0.536	0.515	0.519	0.427
Indonesia	420	6,068	688	0.261	0.179	0.183	0.128
Iraq	53	296	75	0.299	0.290	0.286	0.272
Ireland	46	157,965	5,708	0.158	−0.245	−0.236	−0.179
Israel	123	30,309	1,704	0.240	0.159	0.169	0.102
Italy	359	83,348	5,668	0.223	0.125	0.115	0.057
Jamaica	74	1,554	224	0.280	0.261	0.292	0.234
Japan	2,070	87,523	2,968	−0.026	0.000	0.315	0.363
Jordan	161	4,070	528	0.238	0.173	0.175	0.126
Kazakhstan	186	3,909	273	0.431	0.087	0.074	0.043
Kenya	119	1,167	159	0.417	0.294	0.295	0.205
Kuwait	211	6,360	852	0.154	0.126	0.129	0.112
Kyrgyzstan	22	116	22	0.288	0.251	0.261	0.237
Laos	11	853	37	0.039	0.396	0.400	0.281
Latvia	14	2,512	186	0.217	0.002	0.004	−0.011
Lebanon	67	8,847	617	0.243	0.237	0.240	0.197
Liechtenstein	20	14,199	1,151	0.115	0.098	0.096	0.087
Lithuania	64	2,849	234	0.169	0.081	0.096	0.086
Luxembourg	53	39,556	2,027	0.304	0.198	0.265	0.322
Macedonia	146	302	38	0.132	0.040	0.041	0.034
Malawi	28	256	40	0.634	0.607	0.558	0.395
Malaysia	106	14,569	1,245	0.261	0.164	0.181	0.148
Malta	57	3,496	308	0.580	0.510	0.508	0.378
Mauritius	28	2,719	374	0.245	0.218	0.227	0.190
Mexico	169	21,324	2,493	0.284	0.175	0.220	0.174
Monaco	14	3,890	248	0.209	0.210	0.209	0.209
Montenegro	71	350	37	0.217	0.053	0.074	0.064
Morocco	75	9,459	749	0.267	0.149	0.170	0.103
Namibia	16	1,851	199	0.627	0.565	0.580	0.407
Nepal	208	257	22	0.351	0.285	0.291	0.197
Netherlands	112	232,764	8,134	0.598	0.520	0.527	0.395
New Zealand	2	346	31	0.043	−0.007	−0.007	0.002
Niger	14	169	17	0.350	0.302	0.279	0.187
Nigeria	147	3,741	329	1.264	0.449	0.455	0.350
Norway	219	19,584	1,107	0.212	0.174	0.176	0.131
Oman	121	2,948	367	0.247	0.191	0.190	0.171
Pakistan	167	1,029	83	0.079	0.012	0.083	0.079

The table provides country-specific information about the number of observations and average values of different variables for the sample of international banks between 1999-2013 used in this study. Obs. is the number of bank-year observations, Assets is total book assets, Equity is total book equity, PIOP is Pre-impairment operating profit scaled by beginning-of-the-year common equity, OP is Operating profit scaled by beginning-of-the-year common equity, PTP is Pre-tax profit scaled by beginning-of-the-year common equity, NI is Net income scaled by beginning-of-the-year common equity.

Table 4.3: Country-specific descriptive statistics (continued)

	Obs.	Assets	Equity	PIOP	OP	PTP	NI
Palestine	25	617	74	0.209	0.191	0.192	0.142
Panama	74	3,163	316	0.248	0.180	0.188	0.170
Peru	208	2,982	302	0.434	0.208	0.241	0.169
Philippines	170	5,267	540	0.226	0.184	0.190	0.155
Poland	154	15,055	1,566	0.299	0.190	0.196	0.158
Portugal	70	46,003	2,381	0.218	0.036	0.055	0.031
Qatar	61	15,130	1,983	0.287	0.226	0.231	0.230
Korea	176	56,740	4,284	0.198	0.114	0.116	0.085
Moldova	51	328	52	0.424	0.384	0.372	0.324
Romania	47	5,780	588	0.314	0.196	0.197	0.174
Russia	622	9,468	994	0.299	0.193	0.201	0.140
Saudi Arabia	112	21,653	2,761	0.258	0.217	0.218	0.218
Serbia	221	735	153	0.174	−0.006	0.010	0.007
Singapore	109	44,682	4,072	0.137	0.123	0.132	0.109
Slovakia	75	5,238	450	0.053	0.351	0.348	0.358
Slovenia	68	3,183	243	0.383	0.009	0.046	−0.016
South Africa	158	31,788	2,216	0.420	0.321	0.324	0.296
Spain	117	237,622	13,313	0.261	0.073	0.045	0.005
Sri Lanka	47	988	108	0.278	0.226	0.235	0.157
Swaziland	14	182	21	0.409	0.395	0.395	0.279
Sweden	73	182,014	7,867	0.169	0.154	0.156	0.079
Switzerland	455	79,143	3,386	0.187	0.164	0.155	0.128
Syria	49	880	78	0.202	0.091	0.078	0.063
Taiwan	184	24,116	1,732	0.131	0.070	0.073	0.061
Thailand	348	10,491	832	0.241	0.070	0.070	0.037
Togo	11	9,373	1,007	0.419	0.312	0.316	0.220
Trinidad and T.	38	4,556	625	0.320	0.291	0.295	0.231
Tunisia	182	1,604	145	0.223	0.103	0.108	0.065
Turkey	201	21,755	2,346	0.230	0.171	0.177	0.141
Uganda	40	384	43	0.660	0.590	0.609	0.461
Ukraine	114	1,709	205	0.404	0.093	0.075	0.036
United Arab Em.	224	12,569	1,451	0.247	0.190	0.192	0.191
United Kingdom	670	153,278	6,445	0.238	0.135	0.131	0.114
Tanzania	12	1,092	125	0.424	0.342	0.343	0.245
United States	11,065	20,914	1,380	0.125	0.076	0.075	0.053
Uruguay	3	1,547	−136	6.441	10.448	9.366	9.316
Venezuela	202	5,689	479	0.558	0.439	0.441	0.408
Vietnam	91	6,112	468	0.329	0.247	0.249	0.191
Zambia	59	483	56	0.451	0.288	0.337	0.168
Zimbabwe	26	494	59	0.859	0.674	0.283	0.121

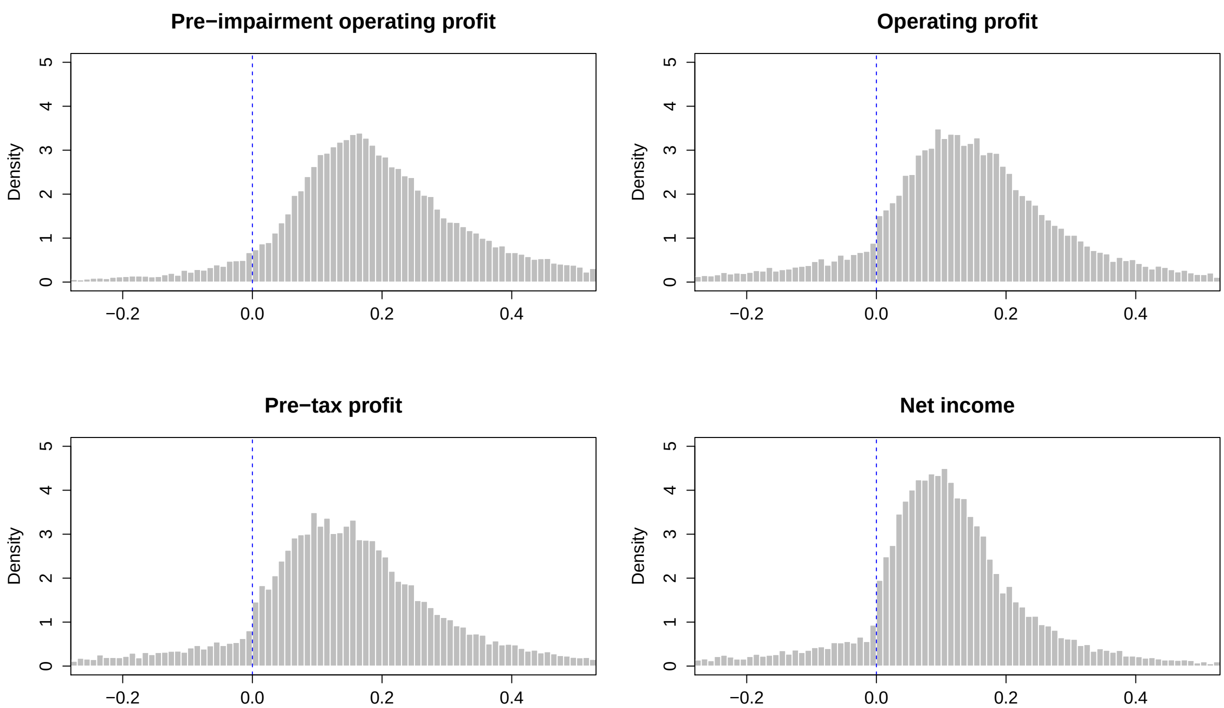
The table provides country-specific information about the number of observations and average values of different variables for the sample of international banks between 1999-2013 used in this study. Obs. is the number of bank-year observations, Assets is total book assets, Equity is total book equity, PIOP is Pre-impairment operating profit scaled by beginning-of-the-year common equity, OP is Operating profit scaled by beginning-of-the-year common equity, PTP is Pre-tax profit scaled by beginning-of-the-year common equity, NI is Net income scaled by beginning-of-the-year common equity.

Table 4.4: Correlation matrix

	OP	PTP	NI	PIOP−NI	PIOP−OP	OP−PTP	PTP−NI
PIOP	0.87***	0.60***	0.45***	0.71***	0.71***	0.28***	0.72***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
OP	1.00	0.78***	0.63***	0.42***	0.27***	0.18***	0.74***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
PTP		1.00	0.96***	−0.12***	0.06***	−0.48***	0.45***
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
NI			1.00	−0.32***	−0.04***	−0.62***	0.19***
				(0.00)	(0.00)	(0.00)	(0.00)
PIOP−NI				1.00	0.78***	0.78***	0.61***
					(0.00)	(0.00)	(0.00)
PIOP−OP					1.00	0.28***	0.34***
						(0.00)	(0.00)
OP−PTP						1.00	0.33***
							(0.00)

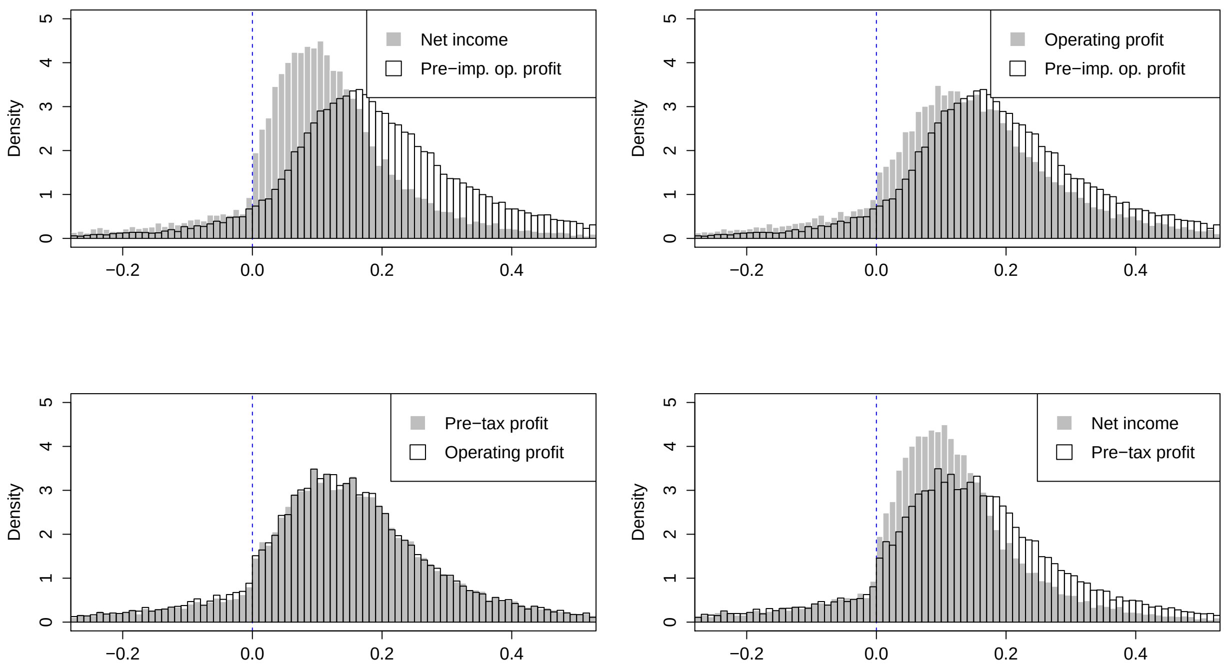
The table shows Pearson's correlation coefficients between the various levels and streams variables used in this study. The sample covers international banks between 1999-2013. PIOP is Pre-impairment operating profit, OP is Operating profit, PTP is Pre-tax profit, NI is Net income, PIOP−NI is Earnings stream between PIOP and NI, PIOP−OP is Earnings stream between PIOP and OP, OP−PTP is Earnings stream between OP and PTP, PTP−NI is Earnings stream between PTP and NI. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Figure 4.6: Histograms of individual earnings measures



The figure shows histograms of various earnings measures for a sample of international banks between 1999-2013. All variables are scaled by beginning-of-the-year common equity. Bin width is set at 0.01 for all histograms. The location of zero earnings is marked by the dashed line.

Figure 4.7: Superimposed histograms of earnings measures



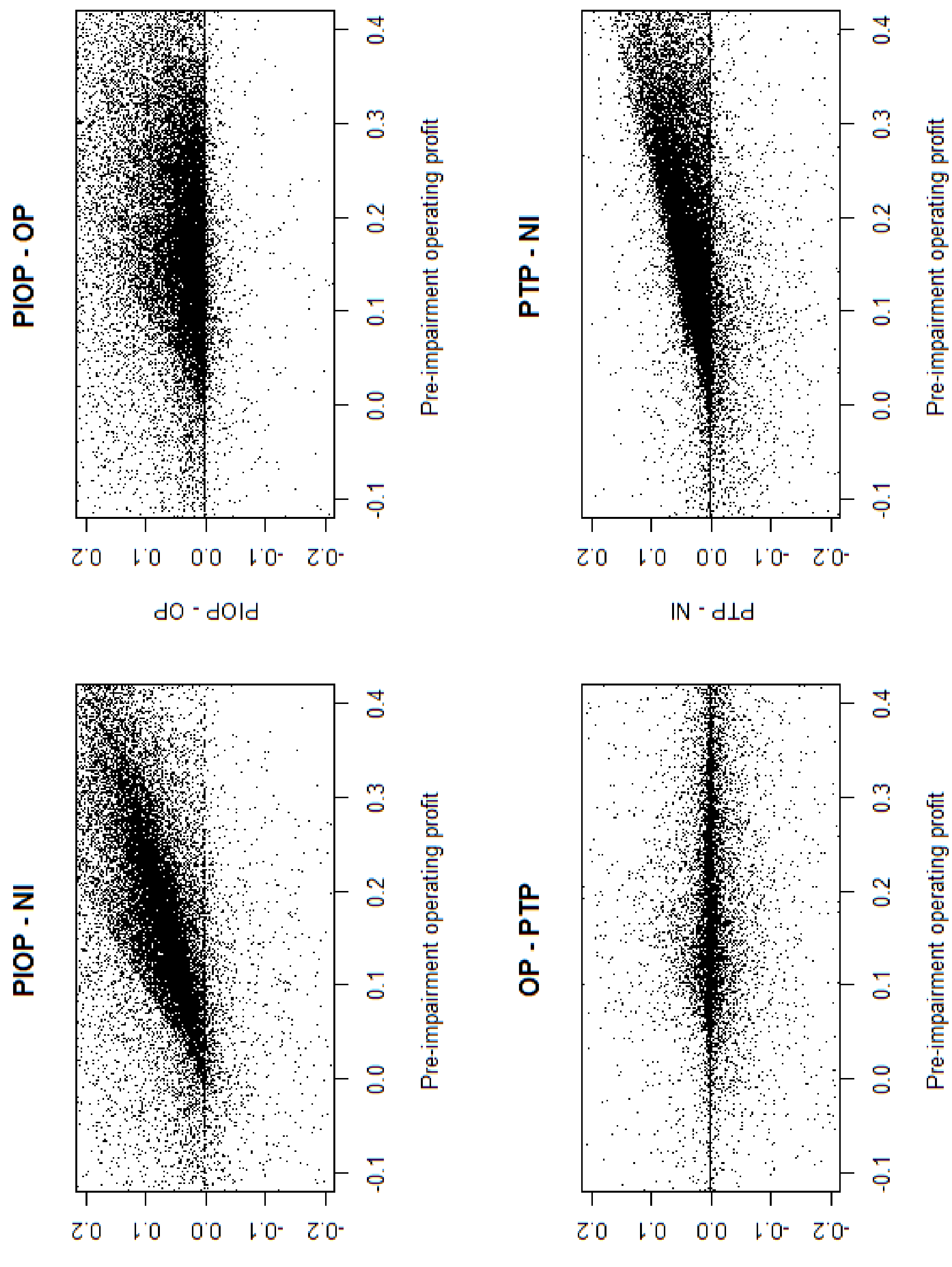
The figure shows superimposed histograms of various earnings measures for a sample of international banks between 1999-2013. All variables are scaled by beginning-of-the-year common equity. Bin width is set at 0.01 for all histograms. The location of zero earnings is marked by the dashed line.

Table 4.5: Earnings management statistics

	Obs.	EM1	EM2	EM3
Pre-impairment operating profit	27,585	0.20	1.19	1.35
Operating profit	27,585	3.45^{***}	3.66^{***}	2.04
Pre-tax profit	27,585	3.88^{***}	5.35^{***}	2.34
Net income	27,585	4.04^{***}	5.42^{***}	2.99

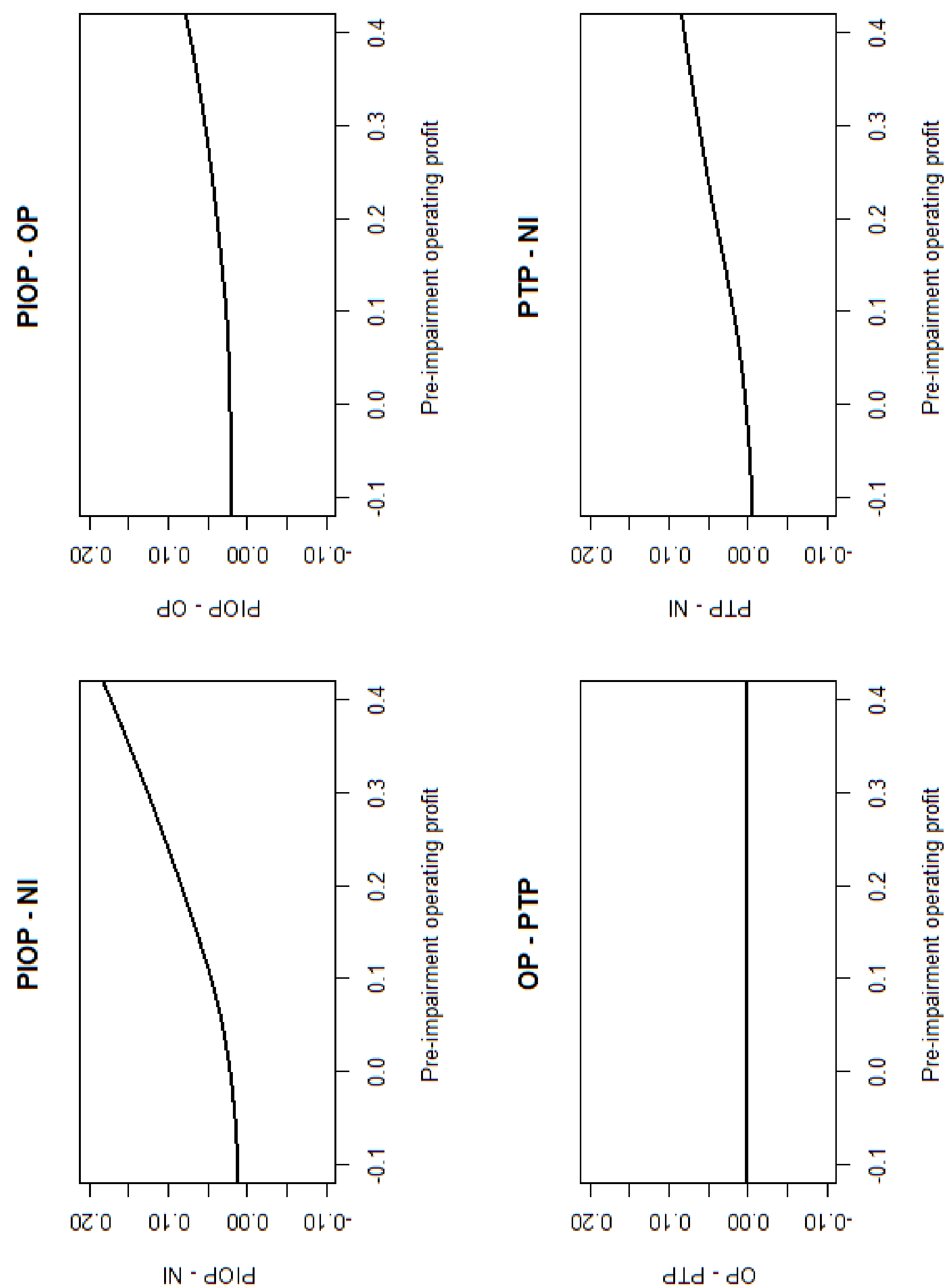
The table shows results of the statistical tests to assess the presence of an irregularity around zero earnings. The sample analysed covers international banks between 1999-2013. Variables are winsorised at the 1% and 99% levels to mitigate the impact of outliers. The null hypothesis is that there is no discontinuity around zero earnings. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$; EM3 is not a statistic but a simple ratio (no significance test computed).

Figure 4.8: Earnings streams plotted as a function of Pre-impairment operating profit



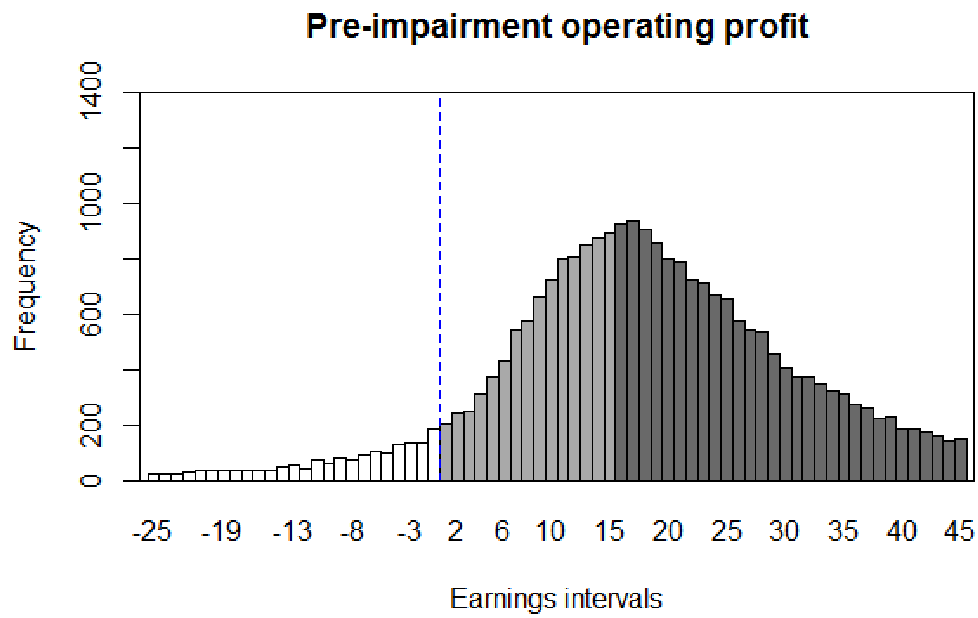
Each scatter plot shows an earnings stream variable plotted as a function of Pre-impairment operating profit. The sample analysed covers international banks between 1999-2013.

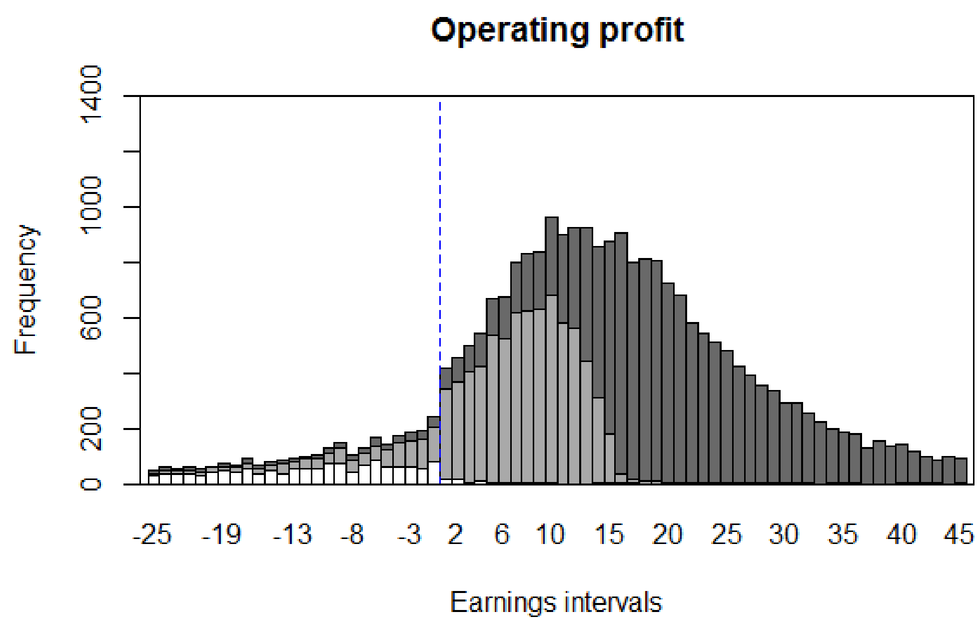
Figure 4.9: Robust regression plots of earnings streams and Pre-impairment operating profit



The figure shows smooth nonparametric regression line based on a locally weighted polynomial regression (LOWESS). In each plot, an earnings stream variable is displayed as a function of Pre-impairment operating profit.

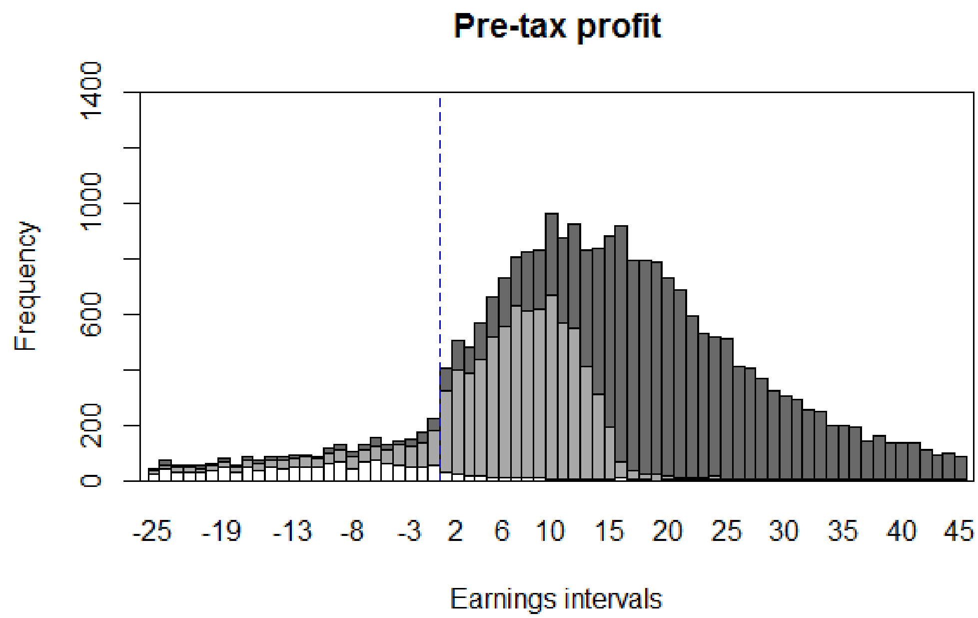
Figure 4.10: Histograms of earnings measures decomposed by earnings groups

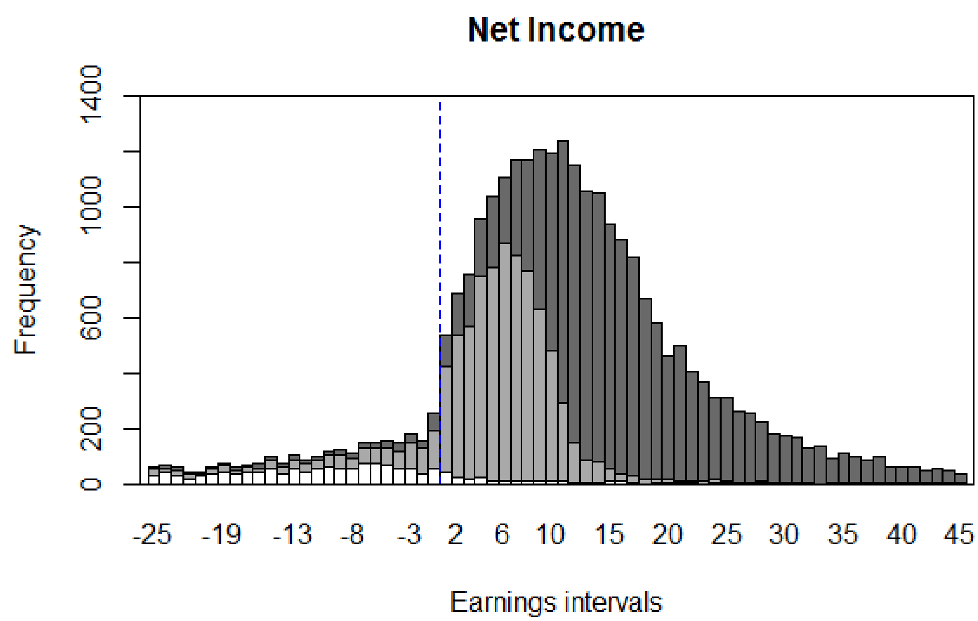




The figure shows histograms of various earnings measures for a sample of international banks between 1999-2013. The various shades of grey refer to the classification as negative earnings banks (white; banks with negative Pre-impairment operating profit), small earnings banks (lightgrey; banks with Pre-impairment operating within the first 15 intervals right to zero) or higher earnings banks (darkgrey; banks with Pre-impairment operating profit located beyond interval 15). All variables are scaled by beginning-of-the-year common equity. Bin width is set at 0.01 for all histograms. The location of zero earnings is marked by the dashed line.

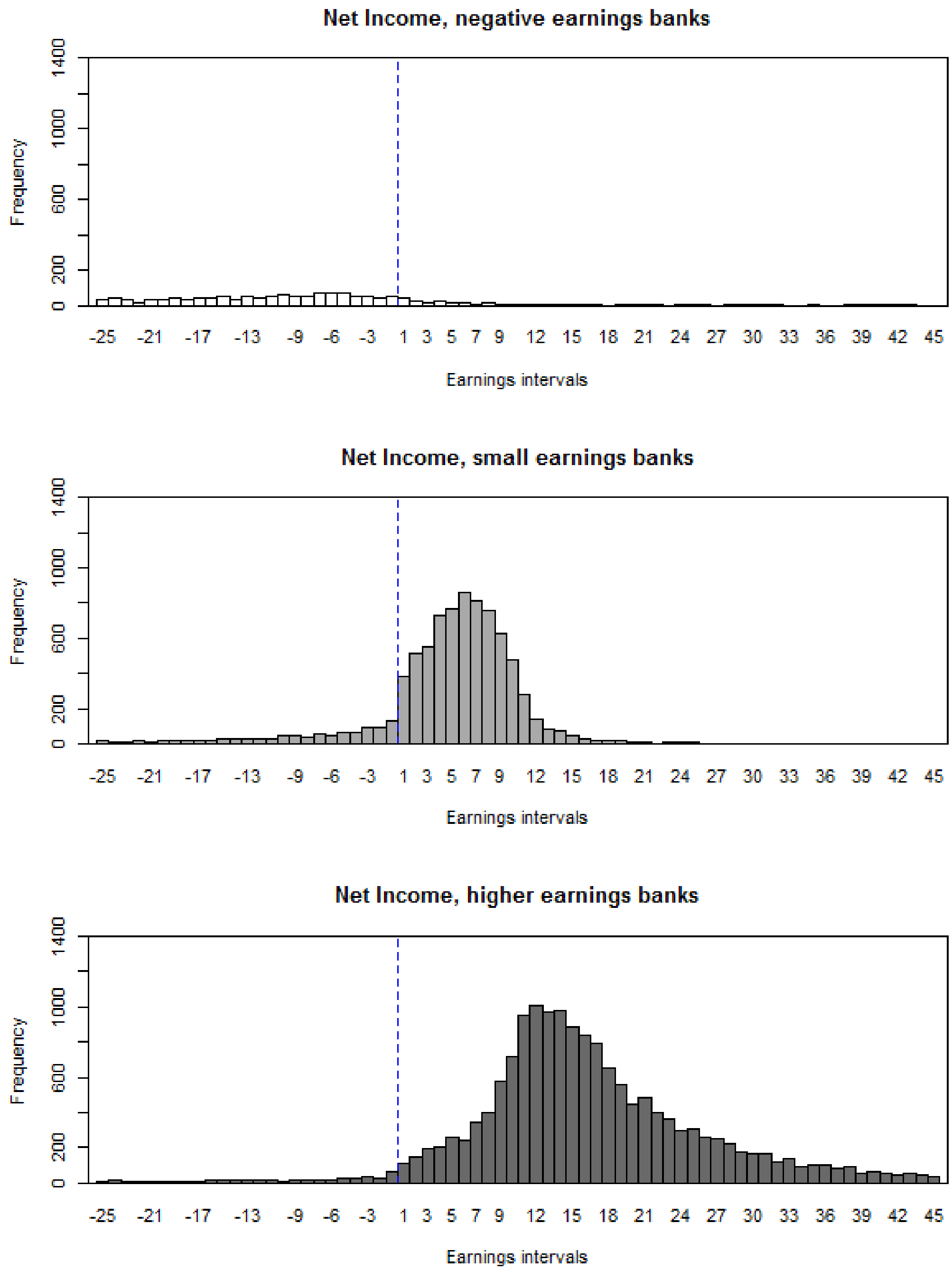
Figure 4.10: Histogram of earnings measures decomposed by earnings groups (continued)





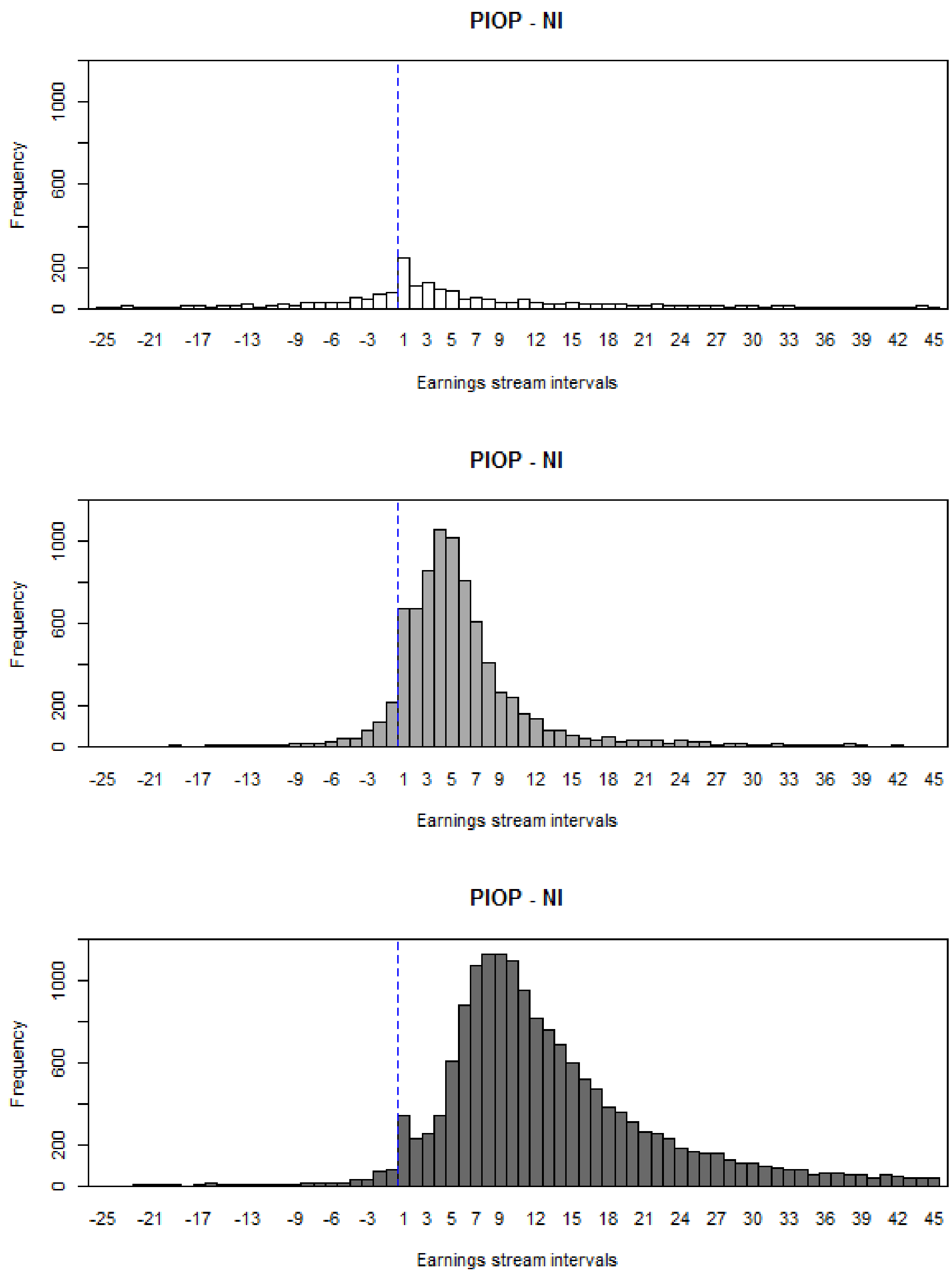
The figure shows histograms of various earnings measures for a sample of international banks between 1999-2013. The various shades of grey refer to the classification as negative earnings banks (white; banks with negative Pre-impairment operating profit), small earnings banks (lightgrey; banks with Pre-impairment operating within the first 15 intervals right to zero) or higher earnings banks (darkgrey; banks with Pre-impairment operating profit located beyond interval 15). All variables are scaled by beginning-of-the-year common equity. Bin width is set at 0.01 for all histograms. The location of zero earnings is marked by the dashed line.

Figure 4.11: Contribution of each earnings group to the distribution of net income



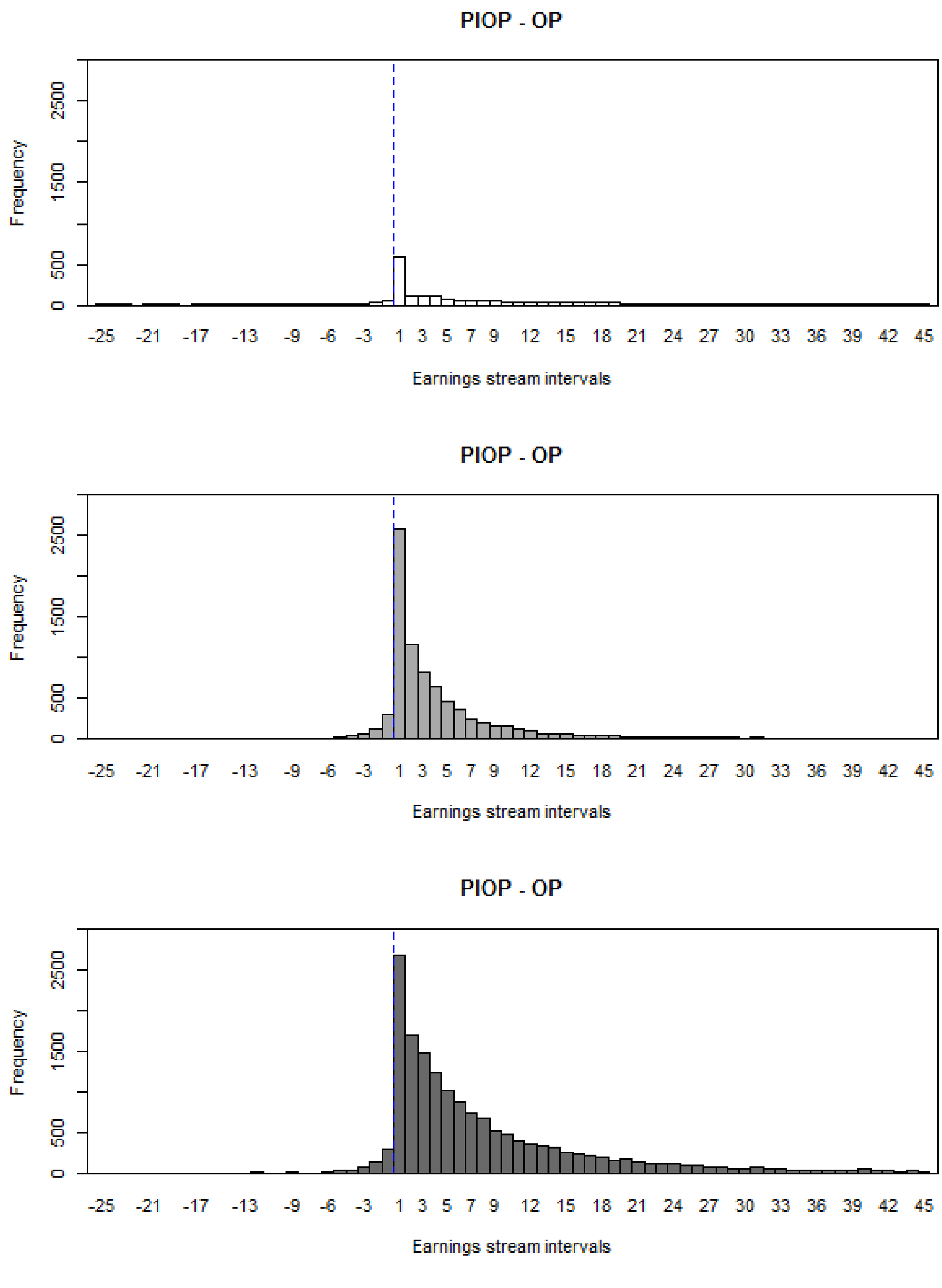
The figure shows the contribution of each earnings group to the distribution of Net income. The sample analysed covers international banks between 1999-2013. The various shades of grey refer to the classification as negative earnings banks (white; banks with negative Pre-impairment operating profit), small earnings banks (lightgrey; banks with Pre-impairment operating within the first 15 intervals right to zero) or higher earnings banks (darkgrey; banks with Pre-impairment operating profit located beyond interval 15). All variables are scaled by beginning-of-the-year common equity. Bin width is set at 0.01 for all histograms. The location of zero earnings is marked by the dashed line.

Figure 4.12: Contribution of each earnings group to the distribution of PIOP−NI



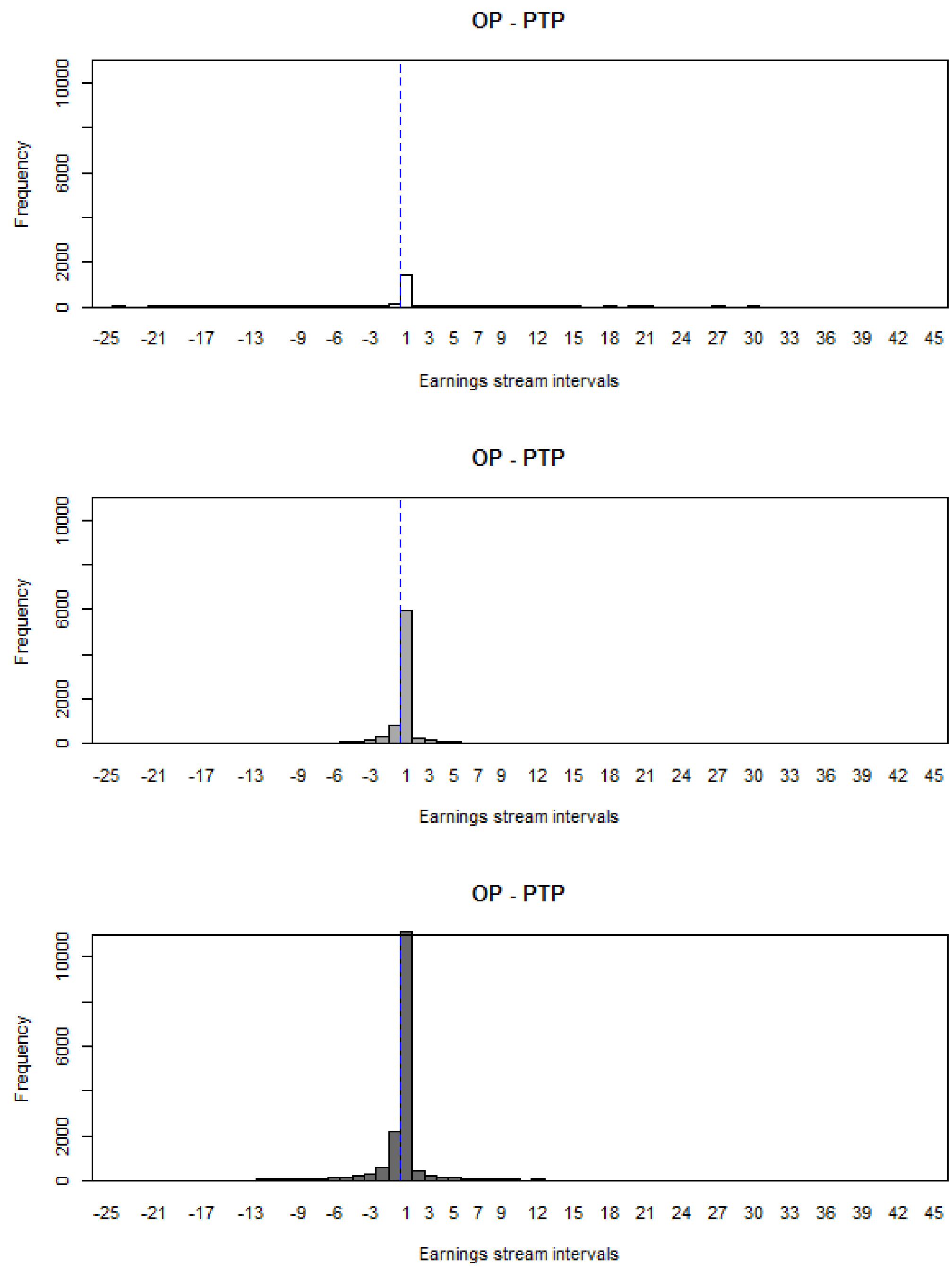
The figure shows the contribution of each earnings group to the distribution of PIOP−NI. The sample analysed covers international banks between 1999-2013. The various shades of grey refer to the classification as negative earnings banks (white; banks with negative Pre-impairment operating profit), small earnings banks (lightgrey; banks with Pre-impairment operating within the first 15 intervals right to zero) or higher earnings banks (darkgrey; banks with Pre-impairment operating profit located beyond interval 15). All variables are scaled by beginning-of-the-year common equity. Bin width is set at 0.01 for all histograms. The location of zero earnings is marked by the dashed line.

Figure 4.13: Contribution of each earnings group to the distribution of PIOP−OP



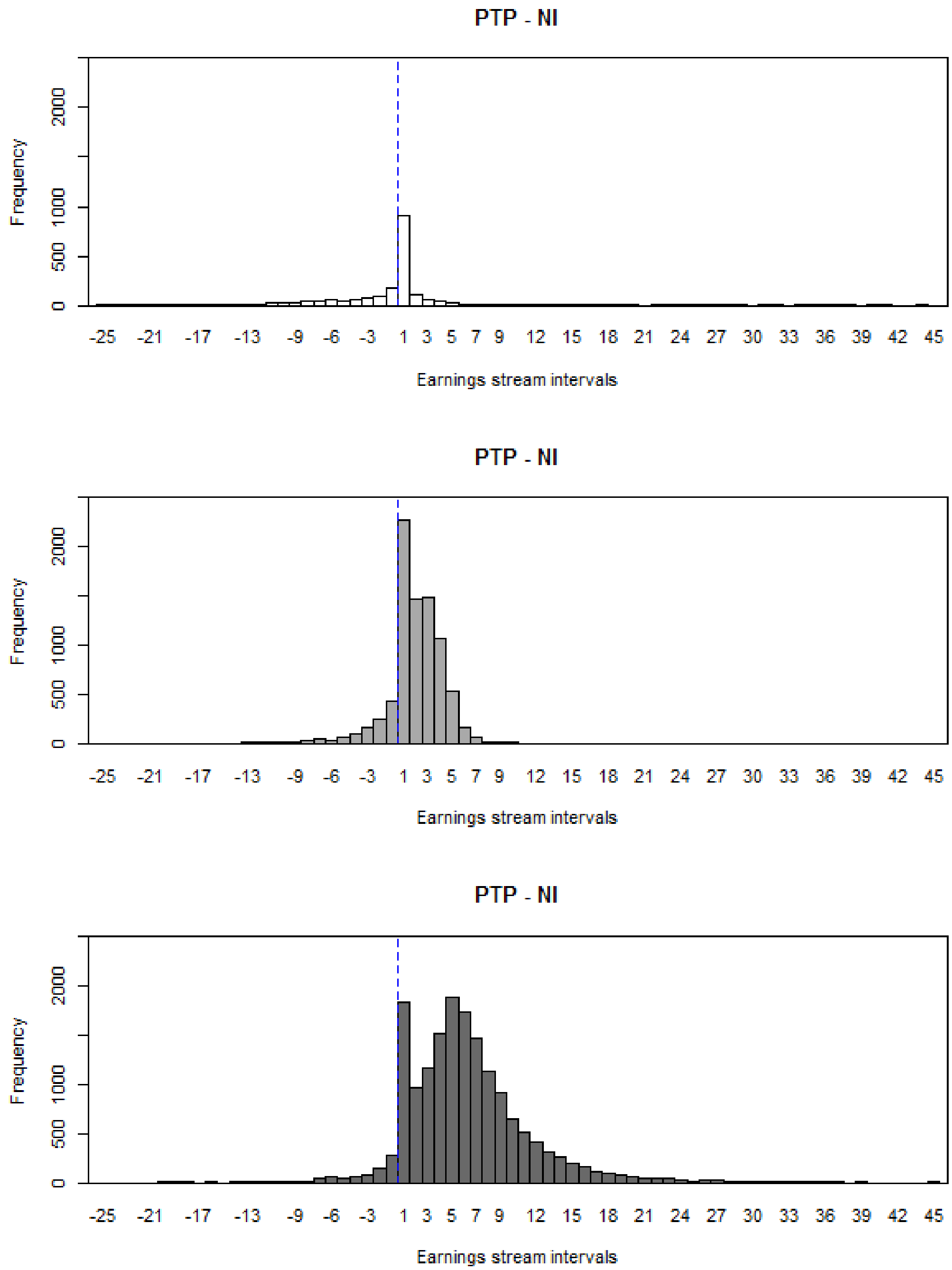
The figure shows the contribution of each earnings group to the distribution of PIOP−OP. The sample analysed covers international banks between 1999-2013. The various shades of grey refer to the classification as negative earnings banks (white; banks with negative Pre-impairment operating profit), small earnings banks (lightgrey; banks with Pre-impairment operating within the first 15 intervals right to zero) or higher earnings banks (darkgrey; banks with Pre-impairment operating profit located beyond interval 15). All variables are scaled by beginning-of-the-year common equity. Bin width is set at 0.01 for all histograms. The location of zero earnings is marked by the dashed line.

Figure 4.14: Contribution of each earnings group to the distribution of OP−PTP



The figure shows the contribution of each earnings group to the distribution of OP−PTP. The sample analysed covers international banks between 1999-2013. The various shades of grey refer to the classification as negative earnings banks (white; banks with negative Pre-impairment operating profit), small earnings banks (lightgrey; banks with Pre-impairment operating within the first 15 intervals right to zero) or higher earnings banks (darkgrey; banks with Pre-impairment operating profit located beyond interval 15). All variables are scaled by beginning-of-the-year common equity. Bin width is set at 0.01 for all histograms. The location of zero earnings is marked by the dashed line.

Figure 4.15: Contribution of each earnings group to the distribution of PTP−NI



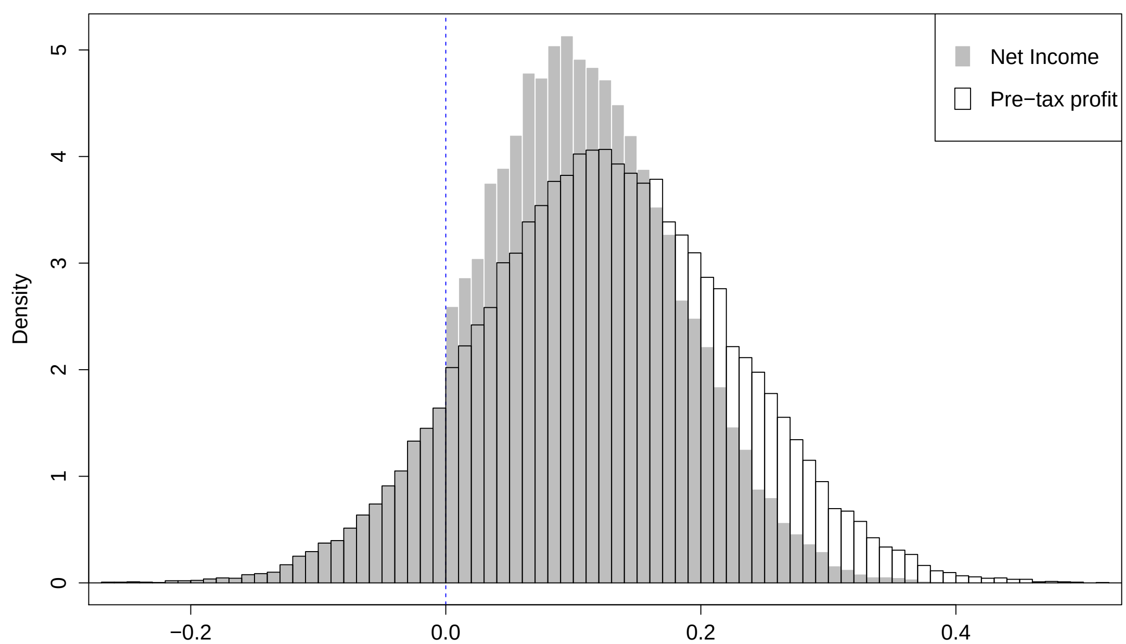
The figure shows the contribution of each earnings group to the distribution of PTP−NI. The sample analysed covers international banks between 1999-2013. The various shades of grey refer to the classification as negative earnings banks (white; banks with negative Pre-impairment operating profit), small earnings banks (lightgrey; banks with Pre-impairment operating within the first 15 intervals right to zero) or higher earnings banks (darkgrey; banks with Pre-impairment operating profit located beyond interval 15). All variables are scaled by beginning-of-the-year common equity. Bin width is set at 0.01 for all histograms. The location of zero earnings is marked by the dashed line.

Table 4.6: Mean difference tests of earnings streams among different earnings groups

	Mean x	Mean y	Diff.
Panel A: PIOP−NI			
Neg. earnings banks (x) − Small earnings banks (y)	−0.7164	0.0632	−0.7796*
	$N = 2134$	$N = 8533$	(0.059)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.7164	0.2237	−0.9401**
	$N = 2134$	$N = 16918$	(0.023)
Small earnings banks (x) − Higher earnings banks (y)	0.0632	0.2237	−0.1605***
	$N = 8533$	$N = 16918$	(0.000)
Panel B: PIOP−OP			
Neg. earnings banks (x) − Small earnings banks (y)	−0.2440	0.0534	−0.2974
	$N = 2134$	$N = 8533$	(0.164)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.2440	0.1410	−0.3851*
	$N = 2134$	$N = 16918$	(0.072)
Small earnings banks (x) − Higher earnings banks (y)	0.0534	0.1410	−0.0877***
	$N = 8533$	$N = 16918$	(0.000)
Panel C: OP−PTP			
Neg. earnings banks (x) − Small earnings banks (y)	−0.3191	−0.0016	−0.3175
	$N = 2134$	$N = 8533$	(0.188)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.3191	0.0010	−0.3201
	$N = 2134$	$N = 16918$	(0.184)
Small earnings banks (x) − Higher earnings banks (y)	−0.0016	0.0010	−0.0026
	$N = 8533$	$N = 16918$	(0.644)
Panel D: PTP−NI			
Neg. earnings banks (x) − Small earnings banks (y)	−0.1533	0.0114	−0.1646***
	$N = 2134$	$N = 8533$	(0.008)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.1533	0.0816	−0.2349***
	$N = 2134$	$N = 16918$	(0.000)
Small earnings banks (x) − Higher earnings banks (y)	0.0114	0.0816	−0.0703***
	$N = 8533$	$N = 16918$	(0.000)

The table shows the mean of the various earnings streams among Negative earnings banks, Small earnings banks, and Higher earnings banks, differences in means across earnings groups, and the number of observations N in each earnings group. For each mean difference, a test statistic (t-test) is computed with p-values reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Negative earnings banks are banks with negative Pre-impairment operating profit, Small earnings banks are banks with Pre-impairment operating profit within the first 15 intervals right to zero, and Higher earnings banks are banks with Pre-impairment operating profit located beyond interval 15, with earnings intervals set at 0.01. The sample analysed covers international banks between 1999-2013.

Figure 4.16: Model calculation of the kinking effect of taxation



The figure shows superimposed histograms of various earnings measures for a randomly selected sample of 30,000 observations with mean of 0.125 and standard deviation of 0.1. The location of zero earnings is marked by the dashed line.

Table 4.7: Earnings management statistics - Robustness tests

	Obs.	EM1	EM2	EM3
Panel A: OECD				
Pre-impairment operating profit	18412	0.70	1.13	1.38
Operating profit	18412	3.07***	3.01***	2.01
Pre-tax profit	18412	1.93*	3.46***	1.99
Net income	18412	1.72*	3.20***	2.42
Panel B: Non-OECD				
Pre-impairment operating profit	9183	−1.29	1.15	1.72
Operating profit	9183	4.29***	7.03***	2.68
Pre-tax profit	9183	6.75***	7.31***	3.92
Net income	9183	5.99***	6.99***	5.71
Panel C: US				
Pre-impairment operating profit	11069	0.07	1.54	1.49
Operating profit	11069	2.55**	4.89***	1.99
Pre-tax profit	11069	1.71*	3.46***	1.74
Net income	11069	1.50	3.06***	2.11
Panel D: Non-US				
Pre-impairment operating profit	16526	0.00	0.85	1.31
Operating profit	16526	3.91***	5.14***	2.23
Pre-tax profit	16526	4.50***	5.33***	3.32
Net income	16526	4.32***	6.93***	4.58
Panel E: Scaled by total assets				
Pre-impairment operating profit	27585	−0.42	0.83	1.53
Operating profit	27585	0.47	3.36***	2.10
Pre-tax profit	27585	1.72*	3.90***	2.61
Net income	27585	2.81***	5.02***	3.80
Panel F: Diversified assets				
Pre-impairment operating profit	23451	0.44	1.00	1.35
Operating profit	23451	3.81***	3.71***	2.24
Pre-tax profit	23451	2.86***	4.53***	2.33
Net income	23451	3.59***	4.63***	3.10

Table 4.7: Earnings management statistics - Robustness tests (continued)

	Obs.	EM1	EM2	EM3
Panel G: Diversified income				
Pre-impairment operating profit	21932	-1.61	0.31	1.17
Operating profit	21932	3.52***	3.27***	2.43
Pre-tax profit	21932	3.37***	4.53***	2.55
Net income	21932	3.41***	5.09***	3.29
Panel H: Alternative measures				
Pre-impairment operating profit	27585	-1.31	1.17	1.58
Operating profit	27585	4.15***	4.03***	2.27
Pre-tax profit	27585	4.92***	5.42***	2.64
Net income	27585	5.51***	6.53***	3.64

The table shows results of the statistical tests to assess the presence of an irregularity around zero earnings. The samples analysed in Panels A to D cover, respectively, banks in OECD countries, banks in non-OECD countries, U.S. banks, and non-U.S. banks. The sample analysed in Panels E to H cover international banks between 1999-2013. Variables are winsorised at the 1% and 99% levels to mitigate the impact of outliers. The null hypothesis is that there is no discontinuity around zero earnings. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$; EM3 is not a statistic but a simple ratio (no significance test computed).

Table 4.8: Mean difference tests of earnings streams among different earnings groups - OECD sample

	Mean x	Mean y	Diff.
Panel A: PIOP−NI			
Neg. earnings banks (x) − Small earnings banks (y)	−1.0177	0.0651	-1.0827^{*}
	$N = 1558$	$N = 6562$	(0.056)
Neg. earnings banks (x) − Higher earnings banks (y)	−1.0177	0.1838	-1.2015^{**}
	$N = 1558$	$N = 10292$	(0.034)
Small earnings banks (x) − Higher earnings banks (y)	0.0651	0.1838	-0.1187^{***}
	$N = 6562$	$N = 10292$	(0.000)
Panel B: PIOP−OP			
Neg. earnings banks (x) − Small earnings banks (y)	−0.4003	0.0527	−0.4529
	$N = 1558$	$N = 6562$	(0.119)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.4003	0.1152	-0.5155^{*}
	$N = 1558$	$N = 10292$	(0.076)
Small earnings banks (x) − Higher earnings banks (y)	0.0527	0.1152	-0.0626^{***}
	$N = 6562$	$N = 10292$	(0.000)
Panel C: OP−PTP			
Neg. earnings banks (x) − Small earnings banks (y)	−0.4242	0.0009	−0.4251
	$N = 1558$	$N = 6562$	(0.198)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.4242	0.0036	−0.4278
	$N = 1558$	$N = 10292$	(0.195)
Small earnings banks (x) − Higher earnings banks (y)	0.0009	0.0036	−0.0027
	$N = 6562$	$N = 10292$	(0.673)
Panel D: PTP−NI			
Neg. earnings banks (x) − Small earnings banks (y)	−0.1932	0.0115	-0.2047^{**}
	$N = 1558$	$N = 6562$	(0.016)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.1932	0.0650	-0.2582^{***}
	$N = 1558$	$N = 10292$	(0.003)
Small earnings banks (x) − Higher earnings banks (y)	0.0115	0.0650	-0.0534^{***}
	$N = 6562$	$N = 10292$	(0.000)

The table shows the mean of the various earnings streams among Negative earnings banks, Small earnings banks, and Higher earnings banks, differences in means across earnings groups, and the number of observations N in each earnings group. For each mean difference, a test statistic (t-test) is computed with p-values reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Negative earnings banks are banks with negative Pre-impairment operating profit, Small earnings banks are banks with Pre-impairment operating profit within the first 15 intervals right to zero, and Higher earnings banks are banks with Pre-impairment operating profit located beyond interval 15, with earnings intervals set at 0.01. The sample analysed covers banks in OECD countries between 1999-2013.

Table 4.9: Mean difference tests of earnings streams among different earnings groups - Non-OECD sample

	Mean x	Mean y	Diff.
Panel A: PIOP−NI			
Neg. earnings banks (x) − Small earnings banks (y)	0.0986	0.0568	0.0418
	$N = 576$	$N = 1975$	(0.604)
Neg. earnings banks (x) − Higher earnings banks (y)	0.0986	0.2855	-0.1869^{**}
	$N = 576$	$N = 6632$	(0.040)
Small earnings banks (x) − Higher earnings banks (y)	0.0568	0.2855	-0.2288^{***}
	$N = 1975$	$N = 6632$	(0.000)
Panel B: PIOP−OP			
Neg. earnings banks (x) − Small earnings banks (y)	0.1787	0.0556	0.1231
	$N = 576$	$N = 1975$	(0.201)
Neg. earnings banks (x) − Higher earnings banks (y)	0.1787	0.1810	−0.0023
	$N = 576$	$N = 6632$	(0.981)
Small earnings banks (x) − Higher earnings banks (y)	0.0556	0.1810	-0.1254^{***}
	$N = 1975$	$N = 6632$	(0.000)
Panel C: OP−PTP			
Neg. earnings banks (x) − Small earnings banks (y)	−0.0348	−0.0097	-0.0252^{***}
	$N = 576$	$N = 1975$	(0.005)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.0348	−0.0029	-0.0319^{**}
	$N = 576$	$N = 6632$	(0.015)
Small earnings banks (x) − Higher earnings banks (y)	−0.0097	−0.0029	−0.0067
	$N = 1975$	$N = 6632$	(0.521)
Panel D: PTP−NI			
Neg. earnings banks (x) − Small earnings banks (y)	−0.0453	0.0108	-0.0561^{**}
	$N = 576$	$N = 1975$	(0.030)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.0453	0.1075	-0.1527^{***}
	$N = 576$	$N = 6632$	(0.000)
Small earnings banks (x) − Higher earnings banks (y)	0.0108	0.1075	-0.0966^{***}
	$N = 1975$	$N = 6632$	(0.000)

The table shows the mean of the various earnings streams among Negative earnings banks, Small earnings banks, and Higher earnings banks, differences in means across earnings groups, and the number of observations N in each earnings group. For each mean difference, a test statistic (t-test) is computed with p-values reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Negative earnings banks are banks with negative Pre-impairment operating profit, Small earnings banks are banks with Pre-impairment operating profit within the first 15 intervals right to zero, and Higher earnings banks are banks with Pre-impairment operating profit located beyond interval 15, with earnings intervals set at 0.01. The sample analysed covers banks in non-OECD countries between 1999-2013.

Table 4.10: Mean difference tests of earnings streams among different earnings groups - U.S. sample

	Mean x	Mean y	Diff.
Panel A: PIOP−NI			
Neg. earnings banks (x) − Small earnings banks (y)	−0.3053	0.0637	−0.3690
	$N = 962$	$N = 3943$	(0.352)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.3053	0.1366	−0.4419
	$N = 962$	$N = 6164$	(0.266)
Small earnings banks (x) − Higher earnings banks (y)	0.0637	0.1366	−0.0730***
	$N = 3943$	$N = 6164$	(0.002)
Panel B: PIOP−OP			
Neg. earnings banks (x) − Small earnings banks (y)	−0.1894	0.0523	−0.2417
	$N = 962$	$N = 3943$	(0.528)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.1894	0.0840	−0.2734
	$N = 962$	$N = 6164$	(0.477)
Small earnings banks (x) − Higher earnings banks (y)	0.0523	0.0840	−0.0317
	$N = 3943$	$N = 6164$	(0.164)
Panel C: OP−PTP			
Neg. earnings banks (x) − Small earnings banks (y)	−0.0083	0.0006	−0.0089**
	$N = 962$	$N = 3943$	(0.041)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.0083	0.0035	−0.0117**
	$N = 962$	$N = 6164$	(0.017)
Small earnings banks (x) − Higher earnings banks (y)	0.0006	0.0035	−0.0028
	$N = 3943$	$N = 6164$	(0.225)
Panel D: PTP−NI			
Neg. earnings banks (x) − Small earnings banks (y)	−0.1077	0.0107	−0.1184
	$N = 962$	$N = 3943$	(0.160)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.1077	0.0492	−0.1568*
	$N = 962$	$N = 6164$	(0.064)
Small earnings banks (x) − Higher earnings banks (y)	0.0107	0.0492	−0.0385***
	$N = 3943$	$N = 6164$	(0.000)

The table shows the mean of the various earnings streams among Negative earnings banks, Small earnings banks, and Higher earnings banks, differences in means across earnings groups, and the number of observations N in each earnings group. For each mean difference, a test statistic (t-test) is computed with p-values reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Negative earnings banks are banks with negative Pre-impairment operating profit, Small earnings banks are banks with Pre-impairment operating profit within the first 15 intervals right to zero, and Higher earnings banks are banks with Pre-impairment operating profit located beyond interval 15, with earnings intervals set at 0.01. The sample analysed covers U.S. banks between 1999-2013.

Table 4.11: Mean difference tests of earnings streams among different earnings groups - Non-U.S. sample

	Mean x	Mean y	Diff.
Panel A: PIOP−NI			
Neg. earnings banks (x) − Small earnings banks (y)	−1.0538	0.0627	−1.1165
	$N = 1172$	$N = 4594$	(0.100)
Neg. earnings banks (x) − Higher earnings banks (y)	−1.0538	0.2736	−1.3273*
	$N = 1172$	$N = 10760$	(0.051)
Small earnings banks (x) − Higher earnings banks (y)	0.0627	0.2736	−0.2108***
	$N = 4594$	$N = 10760$	(0.000)
Panel B: PIOP−OP			
Neg. earnings banks (x) − Small earnings banks (y)	−0.2889	0.0542	−0.3431
	$N = 1172$	$N = 4594$	(0.134)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.2889	0.1737	−0.4625**
	$N = 1172$	$N = 10760$	(0.044)
Small earnings banks (x) − Higher earnings banks (y)	0.0542	0.1737	−0.1195***
	$N = 4594$	$N = 10760$	(0.000)
Panel C: OP−PTP			
Neg. earnings banks (x) − Small earnings banks (y)	−0.5742	−0.0034	−0.5708
	$N = 1172$	$N = 4594$	(0.193)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.5742	−0.0003	−0.5739
	$N = 1172$	$N = 10760$	(0.191)
Small earnings banks (x) − Higher earnings banks (y)	−0.0034	−0.0003	−0.0031
	$N = 4594$	$N = 10760$	(0.725)
Panel D: PTP−NI			
Neg. earnings banks (x) − Small earnings banks (y)	−0.1907	0.0120	−0.2026**
	$N = 1172$	$N = 4594$	(0.025)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.1907	0.1002	−0.2909***
	$N = 1172$	$N = 10760$	(0.002)
Small earnings banks (x) − Higher earnings banks (y)	0.0120	0.1002	−0.0883***
	$N = 4594$	$N = 10760$	(0.000)

The table shows the mean of the various earnings streams among Negative earnings banks, Small earnings banks, and Higher earnings banks, differences in means across earnings groups, and the number of observations N in each earnings group. For each mean difference, a test statistic (t-test) is computed with p-values reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Negative earnings banks are banks with negative Pre-impairment operating profit, Small earnings banks are banks with Pre-impairment operating profit within the first 15 intervals right to zero, and Higher earnings banks are banks with Pre-impairment operating profit located beyond interval 15, with earnings intervals set at 0.01. The sample analysed covers non-U.S. banks between 1999-2013.

Table 4.12: Mean difference tests of earnings streams among different earnings groups - Earnings measures scaled by total assets

	Mean x	Mean y	Diff.
Panel A: PIOP−NI			
Neg. earnings banks (x) − Small earnings banks (y)	0.0072	0.0106	-0.0034^{*}
	$N = 2071$	$N = 24972$	(0.086)
Neg. earnings banks (x) − Higher earnings banks (y)	0.0072	0.0835	-0.0763^{***}
	$N = 2071$	$N = 542$	(0.000)
Small earnings banks (x) − Higher earnings banks (y)	0.0106	0.0835	-0.0729^{***}
	$N = 24972$	$N = 542$	(0.000)
Panel B: PIOP−OP			
Neg. earnings banks (x) − Small earnings banks (y)	0.0125	0.0069	0.0056^{***}
	$N = 2071$	$N = 24972$	(0.000)
Neg. earnings banks (x) − Higher earnings banks (y)	0.0125	0.0391	-0.0265^{***}
	$N = 2071$	$N = 542$	(0.003)
Small earnings banks (x) − Higher earnings banks (y)	0.0069	0.0391	-0.0321^{***}
	$N = 24972$	$N = 542$	(0.000)
Panel C: OP−PTP			
Neg. earnings banks (x) − Small earnings banks (y)	−0.0031	−0.0002	-0.0029^{*}
	$N = 2071$	$N = 24972$	(0.095)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.0031	−0.0040	0.0009
	$N = 2071$	$N = 542$	(0.842)
Small earnings banks (x) − Higher earnings banks (y)	−0.0002	−0.0040	0.0038
	$N = 24972$	$N = 542$	(0.366)
Panel D: PTP−NI			
Neg. earnings banks (x) − Small earnings banks (y)	−0.0022	0.0040	-0.0062^{***}
	$N = 2071$	$N = 24972$	(0.000)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.0022	0.0485	-0.0507^{***}
	$N = 2071$	$N = 542$	(0.000)
Small earnings banks (x) − Higher earnings banks (y)	0.0040	0.0485	-0.0445^{***}
	$N = 24972$	$N = 542$	(0.000)

The table shows the mean of the various earnings streams among Negative earnings banks, Small earnings banks, and Higher earnings banks, differences in means across earnings groups, and the number of observations N in each earnings group. For each mean difference, a test statistic (t-test) is computed with p-values reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Negative earnings banks are banks with negative Pre-impairment operating profit, Small earnings banks are banks with Pre-impairment operating profit within the first 15 intervals right to zero, and Higher earnings banks are banks with Pre-impairment operating profit located beyond interval 15, with earnings intervals set at 0.01. The sample analysed covers international banks between 1999-2013.

Table 4.13: Mean difference tests of earnings streams among different earnings groups - Diversified banks (assets) sample

	Mean x	Mean y	Diff.
Panel A: PIOP−NI			
Neg. earnings banks (x) − Small earnings banks (y)	−0.7364	0.0673	−0.8037
	$N = 1553$	$N = 7224$	(0.126)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.7364	0.2186	−0.9550*
	$N = 1553$	$N = 14674$	(0.069)
Small earnings banks (x) − Higher earnings banks (y)	0.0673	0.2186	−0.1512***
	$N = 7224$	$N = 14674$	(0.000)
Panel B: PIOP−OP			
Neg. earnings banks (x) − Small earnings banks (y)	−0.3158	0.0557	−0.3715
	$N = 1553$	$N = 7224$	(0.201)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.3158	0.1429	−0.4587
	$N = 1553$	$N = 14674$	(0.115)
Small earnings banks (x) − Higher earnings banks (y)	0.0557	0.1429	−0.0872***
	$N = 7224$	$N = 14674$	(0.000)
Panel C: OP−PTP			
Neg. earnings banks (x) − Small earnings banks (y)	−0.2985	−0.0011	−0.2974
	$N = 1553$	$N = 7224$	(0.325)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.2985	−0.0015	−0.2970
	$N = 1553$	$N = 14674$	(0.326)
Small earnings banks (x) − Higher earnings banks (y)	−0.0011	−0.0015	0.0004
	$N = 7224$	$N = 14674$	(0.947)
Panel D: PTP−NI			
Neg. earnings banks (x) − Small earnings banks (y)	−0.1221	0.0127	−0.1348**
	$N = 1553$	$N = 7224$	(0.021)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.1221	0.0772	−0.1993***
	$N = 1553$	$N = 14674$	(0.001)
Small earnings banks (x) − Higher earnings banks (y)	0.0127	0.0772	−0.0645***
	$N = 7224$	$N = 14674$	(0.000)

The table shows the mean of the various earnings streams among Negative earnings banks, Small earnings banks, and Higher earnings banks, differences in means across earnings groups, and the number of observations N in each earnings group. For each mean difference, a test statistic (t-test) is computed with p-values reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Negative earnings banks are banks with negative Pre-impairment operating profit, Small earnings banks are banks with Pre-impairment operating profit within the first 15 intervals right to zero, and Higher earnings banks are banks with Pre-impairment operating profit located beyond interval 15, with earnings intervals set at 0.01. The sample analysed covers international banks between 1999-2013.

Table 4.14: Mean difference tests of earnings streams among different earnings groups - Diversified banks (income) sample

	Mean x	Mean y	Diff.
Panel A: PIOP−NI			
Neg. earnings banks (x) − Small earnings banks (y)	−1.5768	0.0652	−1.6420*
	$N = 1044$	$N = 6415$	(0.052)
Neg. earnings banks (x) − Higher earnings banks (y)	−1.5768	0.2341	−1.8109**
	$N = 1044$	$N = 14473$	(0.032)
Small earnings banks (x) − Higher earnings banks (y)	0.0652	0.2341	−0.1689***
	$N = 6415$	$N = 14473$	(0.000)
Panel B: PIOP−OP			
Neg. earnings banks (x) − Small earnings banks (y)	−0.6470	0.0536	−0.7006
	$N = 1044$	$N = 6415$	(0.108)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.6470	0.1521	−0.7991*
	$N = 1044$	$N = 14473$	(0.067)
Small earnings banks (x) − Higher earnings banks (y)	0.0536	0.1521	−0.0985***
	$N = 6415$	$N = 14473$	(0.000)
Panel C: OP−PTP			
Neg. earnings banks (x) − Small earnings banks (y)	−0.6337	−0.0014	−0.6323
	$N = 1044$	$N = 6415$	(0.199)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.6337	0.0038	−0.6376
	$N = 1044$	$N = 14473$	(0.196)
Small earnings banks (x) − Higher earnings banks (y)	−0.0014	0.0038	−0.0052
	$N = 6415$	$N = 14473$	(0.317)
Panel D: PTP−NI			
Neg. earnings banks (x) − Small earnings banks (y)	−0.2961	0.0131	−0.3091**
	$N = 1044$	$N = 6415$	(0.015)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.2961	0.0781	−0.3742***
	$N = 1044$	$N = 14473$	(0.004)
Small earnings banks (x) − Higher earnings banks (y)	0.0131	0.0781	−0.0651***
	$N = 6415$	$N = 14473$	(0.000)

The table shows the mean of the various earnings streams among Negative earnings banks, Small earnings banks, and Higher earnings banks, differences in means across earnings groups, and the number of observations N in each earnings group. For each mean difference, a test statistic (t-test) is computed with p-values reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Negative earnings banks are banks with negative Pre-impairment operating profit, Small earnings banks are banks with Pre-impairment operating profit within the first 15 intervals right to zero, and Higher earnings banks are banks with Pre-impairment operating profit located beyond interval 15, with earnings intervals set at 0.01. The sample analysed covers international banks between 1999-2013.

Table 4.15: Mean difference tests of earnings streams among different earnings groups - First alternative definition of earnings groups

	Mean x	Mean y	Diff.
Panel A: PIOP−NI			
Neg. earnings banks (x) − Small earnings banks (y)	−0.7164	0.0712	−0.7876*
	N = 2134	N = 12953	(0.057)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.7164	0.2722	−0.9885**
	N = 2134	N = 12498	(0.017)
Small earnings banks (x) − Higher earnings banks (y)	0.0712	0.2722	−0.2009***
	N = 12953	N = 12498	(0.000)
Panel B: PIOP−OP			
Neg. earnings banks (x) − Small earnings banks (y)	−0.2440	0.0544	−0.2984
	N = 2134	N = 12953	(0.162)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.2440	0.1710	−0.4150*
	N = 2134	N = 12498	(0.053)
Small earnings banks (x) − Higher earnings banks (y)	0.0544	0.1710	−0.1167***
	N = 12953	N = 12498	(0.000)
Panel C: OP−PTP			
Neg. earnings banks (x) − Small earnings banks (y)	−0.3191	−0.0007	−0.3184
	N = 2134	N = 12953	(0.186)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.3191	0.0011	−0.3201
	N = 2134	N = 12498	(0.184)
Small earnings banks (x) − Higher earnings banks (y)	−0.0007	0.0011	−0.0017
	N = 12953	N = 12498	(0.818)
Panel D: PTP−NI			
Neg. earnings banks (x) − Small earnings banks (y)	−0.1533	0.0176	−0.1708***
	N = 2134	N = 12953	(0.006)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.1533	0.1001	−0.2533***
	N = 2134	N = 12498	(0.000)
Small earnings banks (x) − Higher earnings banks (y)	0.0176	0.1001	−0.0825***
	N = 12953	N = 12498	(0.000)

The table shows the mean of the various earnings streams among Negative earnings banks, Small earnings banks, and Higher earnings banks, differences in means across earnings groups, and the number of observations N in each earnings group. For each mean difference, a test statistic (t-test) is computed with p-values reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Negative earnings banks are banks with negative Pre-impairment operating profit, Small earnings banks are banks with Pre-impairment operating profit within the first 15 intervals right to zero, and Higher earnings banks are banks with Pre-impairment operating profit located beyond interval 20, with earnings intervals set at 0.01. The sample analysed covers international banks between 1999-2013.

Table 4.16: Mean difference tests of earnings streams among different earnings groups - Second alternative definition of earnings groups

	Mean x	Mean y	Diff.
Panel A: PIOP−NI			
Neg. earnings banks (x) − Small earnings banks (y)	−0.7164	0.0584	−0.7747*
	N = 2134	N = 4303	(0.061)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.7164	0.1926	−0.9090**
	N = 2134	N = 21148	(0.028)
Small earnings banks (x) − Higher earnings banks (y)	0.0584	0.1926	−0.1342***
	N = 4303	N = 21148	(0.000)
Panel B: PIOP−OP			
Neg. earnings banks (x) − Small earnings banks (y)	−0.2440	0.0563	−0.3003
	N = 2134	N = 4303	(0.160)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.2440	0.1229	−0.3669*
	N = 2134	N = 21148	(0.086)
Small earnings banks (x) − Higher earnings banks (y)	0.0563	0.1229	−0.0666***
	N = 4303	N = 21148	(0.000)
Panel C: OP−PTP			
Neg. earnings banks (x) − Small earnings banks (y)	−0.3191	−0.0028	−0.3163
	N = 2134	N = 4303	(0.189)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.3191	0.0008	−0.3199
	N = 2134	N = 21148	(0.184)
Small earnings banks (x) − Higher earnings banks (y)	−0.0028	0.0008	−0.0036
	N = 4303	N = 21148	(0.453)
Panel D: PTP−NI			
Neg. earnings banks (x) − Small earnings banks (y)	−0.1533	0.0049	−0.1582**
	N = 2134	N = 4303	(0.011)
Neg. earnings banks (x) − Higher earnings banks (y)	−0.1533	0.0689	−0.2222***
	N = 2134	N = 21148	(0.000)
Small earnings banks (x) − Higher earnings banks (y)	0.0049	0.0689	−0.0640***
	N = 4303	N = 21148	(0.000)

The table shows the mean of the various earnings streams among Negative earnings banks, Small earnings banks, and Higher earnings banks, differences in means across earnings groups, and the number of observations N in each earnings group. For each mean difference, a test statistic (t-test) is computed with p-values reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Negative earnings banks are banks with negative Pre-impairment operating profit, Small earnings banks are banks with Pre-impairment operating profit within the first 15 intervals right to zero, and Higher earnings banks are banks with Pre-impairment operating profit located beyond interval 10, with earnings intervals set at 0.01. The sample analysed covers international banks between 1999-2013.

Chapter 5

Conclusion

In this thesis, we investigated three different aspects of banking. The three independent but related papers that form this thesis are organised in such a way that they can be read independently. We start this concluding chapter with a general overview of the banking industry. We then discuss each paper in more detail in the form of three extended abstracts. We close this thesis with some thoughts on shadow banking.

Brief overview of the banking industry

The banking industry is particularly important for overall economic activity since it channels funds from individuals who save to individuals with productive investment opportunities. However, this central role performed by the banking industry can be double-hedged. While a well-functioning banking system can efficiently promote economic growth, dysfunctions in this industry can severely impact on economic activity. The Great Depression of the 1930s, and more recently the Great Recession, are two dramatic examples.

The banking sector has long been considered as rather boring and unattractive, notably because of tight regulations that strictly limited the range of business activities conducted by banks. However, a worldwide wave of deregulation that started in the 1980s, coupled with technological developments, has dramatically changed the visage of the banking industry. These changes have resulted in the banking industry being populated by a wide variety of banks all around the world.

Banks are different from firms in other industries in several ways. The banking industry is notably characterised by a high degree of regulation, a high degree of leverage, and key accounting positions differing from the nonfinancial industry. These differences reduce the comparability between banks and nonfinancial firms. As a result, banks are often excluded from empirical studies in accounting and finance (e.g. asset pricing, earnings management). Therefore, several areas of research remain largely unexplored for the banking industry. The exclusion of banks from major studies, combined with the particular character of this industry, has given rise to a banking-specific literature.

This thesis has taken advantage of the particular characteristics of the banking industry as well as the exclusion of banks from major studies in the accounting and finance literature. The first two studies take a market approach to analyse the impact of various bank-level characteristics on, respectively, market valuation and stock market returns. The third study, by investigating earnings management, addresses a potential source of distortion affecting information available to and analysed by various market participants and other stakeholders.

The valuation of diversified banks: New evidence

In this study, we analyse the association between a bank and its valuation using a comprehensive sample of international banks including 19,677 bank-year observations between 1998-2013. This association is important for the governance of banks and for banking regulation. While diversification may allow economies of scope and synergies between the different business units of a bank, it may also result in conflicts of interest and agency costs.

Two closely related measures, based on the share of interest income in total operating income, are particularly important to assess the association between diversification and valuation: a diversification proxy that reaches a maximum at an interest-income share of 50% and a type proxy that increases monotonically with interest-income share.[1] The first measure distinguishes between specialised institutions (commercial or investment banks) and diversified institutions (mix of commercial and investment activities). Diversification, however, does not distinguish between full specialisation in commercial activities or full specialisation in investment activities, but considers both types of banks as specialised institutions. The second measure, type, focuses on this distinction. If the type variable is not included, a triangular structure of the diversification variable is imposed on the data since both types of specialised banks are given the same diversification value.[2] In this case, it is not possible to analyse whether banks focusing mainly on investment activities are valued differently compared to banks focusing on commercial activities. The two measures should be jointly considered and their combined effect analysed in empirical studies.

Our study is motivated by the fact that three studies in the recent literature have reported

[1] Alternatively, the share of interest income in total operating income can be replaced by the share of loan assets in total assets.

[2] The diversification effect, by construction, has a symmetrical triangular structure (V-shape or inverted V-shape) because the effect is strongest for interest income share of 0.5, and falls off towards investment banks (share of 0) and commercial banks (share of 1). When bank type is also relevant for valuation, there is a second effect running monotonically from an interest-income share of 0 (pure investment banks) to a level of 1 (pure commercial banks).

strongly different results: Laeven and Levine (2007) found a significant diversification *discount* for a sample of U.S. banks between 1998-2002, Baele et al. (2007) reported a significant diversification *premium* for a sample of European banks between 1989-2004, and Elsas et al. (2010) found no *direct effect*, but an *indirect effect* from a positive association of diversification with profitability for a sample of banks from nine developed countries. Of course, the difference in results between these studies could be explained by the geographical composition of the samples or by the time periods analysed. For instance, Baele et al. (2007) advanced that regulatory or institutional differences were responsible for the different results found in their study compared to the study of Laeven and Levine (2007). However, a more careful analysis of the three studies reveals fundamental methodological differences that may be responsible for the different results found.

First, there are two major issues regarding the use of type and diversification: Only Laeven and Levine (2007) systematically include these two variables in regression. In the two other studies, either type and diversification are not jointly included, or when they are, type does not capture the common understanding of bank type as in Laeven and Levine (2007), i.e. a monotonically and regular increase of the type value when interest income share increases.[3] The various diversification proxies used in the three studies are, however, fairly similar to each other. Second, Elsas et al. (2010) used an estimation approach with bank fixed effect, thus focusing on the variation of individual bank value over time, while Laeven and Levine (2007) and Baele et al. (2007) used country fixed effects and are primarily interested in cross-sectional valuation differences. And third, the control variables used are not identical. For instance, Elsas et al. (2010) argued that including a profitability variable absorbed the valuation effect of diversification.[4]

In this study, we aim to reconcile the different results from previous studies by using a comprehensive framework with unified time periods, estimation approach, proxies for diversification and type, and control variables. With this unified framework, we aim to shed new light on the different results found in these three studies, i.e. whether these results are driven by institutional and regulatory determinants of diversification, or whether they are caused by differences in method-

[3]For example, one measure of type used has a peculiar form going to infinity when interest-income share approaches one, which implies that tiny changes of interest-income share yield large changes in type.

[4]"*When controlling for profitability, bank market value is not directly affected by diversification*" (Elsas et al., 2010, p. 1286).

ology. To do so, we build three subsets of banks corresponding to the samples used in the three prior studies of interest. In addition, we divide the total period into four subperiods to detect a possible evolution over time. We summarise the estimation results in tabular and graphical form to highlight the combined effect of type and diversification (predicted partial response of valuation to type and diversification).

We employ Tobin's Q as our valuation proxy. We use the same income-based and asset-based measures of bank type and diversification as in Laeven and Levine (2007). The type variable is defined as the ratio of net interest income to total operating income (or loans relative to total earning assets). Diversification is defined as one minus the absolute value of the ratio of net interest income minus other operating income divided by total operating income (or one minus the absolute value of the ratio of net loans minus other earning assets divided by total earnings assets). We further include bank-level control variables that account for a banks' funding structure, its operating profitability, bank-efficiency, loan losses provisions, risk, growth opportunities, size, and equity. Finally, we include macroeconomic and regulatory control variables and use country and year fixed effects.

Our main results can be summarised as follows. In each subperiod, the effects of type and diversification are fairly similar for the three subsamples of the main prior studies. Thus, the diversification effect does not seem to be influenced by regulatory or institutional factors. In the first subperiod (1998-2002), we find a significant valuation premium for investment banks and a significant diversification discount that both confirm the findings of Laeven and Levine (2007). The graphical representation of the joint effect of type and diversification shows that the diversification discount is mainly driven by a small number of rather extreme observations for banks with an investment profile. The effect is considerably smaller in a robust regression. Among commercial banks, valuation is not systematically related to the share of investment banking activities. Thus, as long as the investment activities are not predominant, they are not rewarded by a valuation premium. After the first period, the diversification discount and the type effect drop substantially. Both effects practically vanish in the last subperiod (2010-2013).

Beyond the thematic of diversification, our paper shows the importance of using similar methodological frameworks when similar topics are investigated. This is necessary to guarantee the comparability of the results. Otherwise, it is fairly difficult to assess whether differences between studies are genuine and can be attributed to e.g. institutional or regulatory factors, or whether they come from methodological choices. If results from studies treating the same thematic are not directly comparable, one risks drawing the wrong conclusion. Finally, our study underlines the importance of replicating existing studies, e.g. when these existing studies come to strongly different results.

Profitability and other industry-specific determinants of banks' cross-sectional returns

This study investigates the predicting power of profitability, industry-specific variables, and traditional market anomalies on the cross-section of bank stock returns. Our final sample includes 190,592 monthly returns for U.S. banks between 1980-2014. The profitability premium that relates more profitable firms to higher stock returns has long been one of the least explored market anomaly. In the past few years, however, it has attracted particular attention from the academic literature. Several studies (e.g. Hou et al. (in press); Novy-Marx (2013)) have highlighted the strong predicting power of profitability. Moreover, Fama and French (2014) have extended their three-factor model to a five-factor model including a profitability-based factor.

Banks are typically excluded from asset pricing studies because they are different from firms in other industries. Thus, the existence of the profitability premium, as well as other market anomalies, remains largely unknown for a sizeable portion of listed companies. Furthermore, because of the different nature of banks compared to firms in other industries, there may exist important links between industry-specific variables and the cross-section of stock returns (Cooper et al., 2003). Finally, since we include control variables accounting for well-known market anomalies such as size, book-to-market, or past performance at different horizons, this study also provides evidence about the predicting power of these anomalies in the banking industry.

Only few studies have investigated the predicting power of market anomalies in the banking industry. These studies are limited to book-to-market and size. Some of them have documented the existence of size and book-to-market premiums (e.g. Baek and Bilson (2014); Barber and Lyon (1997)) similar to the nonfinancial industry, others (e.g. Cooper et al. (2003); Viale et al. (2009))

found no effect. While they all used U.S. data, they did not cover the same time periods, which may be the reason why they have come to different results. To our knowledge, the predicting power of profitability and momentum have never been explored within the banking industry. As for the predicting power of banking industry-specific variables on the cross-section of expected returns, no study has, to our knowledge, been conducted so far. Only Cooper et al. (2003) have covered a related topic by trying to relate quarterly changes in industry-specific variables to stock returns in order to analyse the impact of good/bad news shocks.

In the empirical analysis, there is no consensus regarding the best measure of economic profitability. While Novy-Marx (2013) used gross profit divided by total assets, Fama and French (2006, 2008) used income before extraordinary items divided by book value of equity. We use several profitability proxies covering several earnings positions and profitability aspects down the income statement, namely Pre-impairment income scaled by total assets, Operating income scaled by total assets, Pre-tax income scaled by total assets, and Net income scaled by book equity. We consider several industry-specific variables, namely loan loss provisions scaled by total assets, the ratio of loans to total earnings assets, the degree of asset diversification, the ratio of customers' deposits to total liabilities, and common equity scaled by total assets. Finally, we include control variables accounting for well-known market anomalies such as book-to-market, size, past performance at a horizon of one month (short-term return reversal), and past performance at a horizon of twelve to two months (momentum).

In order to assess the predicting power of the various explanatory variables on the cross-section of monthly returns, we use three main methods. First, we look at average monthly returns for portfolios formed on one-way sorts, and then at the results of Fama and MacBeth (1973) monthly cross-sectional regression. We further analyse intercepts from the four-factor model of Carhart (1997) to investigate the presence of excess returns above and beyond those suggested by the four-factor model. We also employ portfolios' Sharpe ratios to examine whether cross-sectional profitability is due to increasing risk. In addition, we conduct several robustness tests of our results. Namely, we increase the number of control variables per specification, we use an alternative approach to address extreme values, we consider the possibility that our results may be driven by small caps, and we look at the evolution of the coefficient estimates over time.

Our main results are as follows. First, we find mixed evidence regarding the predicting power of profitability. Evidence from Fama and MacBeth (1973) cross-sectional regression suggests a positive relationship between profitability and expected stock returns. However, further analysis shows that small market capitalisations are very influential in explaining this result; once the smallest market capitalisations are excluded from the analysis, the statistical significance of the relationship disappears. In addition, results from one-way sorts of returns on profitability are largely inconclusive and do not point to the existence of a profitability premium. Similarly, evidence indicating the presence of abnormal returns suggested by significant intercepts of long−short portfolios regressed on the four-factor model of Carhart (1997) are very limited. These findings contrast with recent, clear-cut evidence from Novy-Marx (2013) suggesting that profitability is a strong predictor of expected cross-sectional returns. Thus, the profitability premium seems to be much more pronounced among nonfinancial firms than it is in the banking industry.

Second, among traditional market anomalies, we find evidence suggesting that book-to-market, size, and past performance at a horizon of one month can predict the cross-section of expected returns. Results regarding past performance at a horizon of one month, suggesting short-term return reversal, stand out from the other variables considered in terms of economic and statistical significance. In the one-way sort portfolios, we find an average monthly return of 2.079% for the long−short portfolio as well as a statistically significant intercept suggesting excess returns of 2.12% in the time series regression. In Fama and MacBeth (1973) cross-sectional regression, the statistical significance of this variable stands out as well. Finally, the effect is particularly stable over time and persistent in all portfolios sorted on size, meaning that this short-term return reversal does not result from high volume transactions among small, illiquid stocks. We also find convincing evidence regarding the predicting power of book-to-market. As for the predicting power of size, it appears to be, similar to profitability, largely driven by the smallest market capitalisations. Finally, our results do not suggest that past performance at a horizon of two to 12 months (momentum) can effectively predict expected stock returns.

And third, for industry-specific variables, our results show that loan loss provisions, loan share, and activity diversification can all predict the cross-section of expected stock returns. Banks with a lower ratio of loan loss provisions to total assets, a lower share of loans to total earnings assets, and a higher degree of assets diversification are associated with higher returns. We find convincing evidence in most of our tests (Fama and MacBeth (1973) regression, one-way sort portfolios, intercepts from time series regression). Finally, we find only limited evidence regarding the predicting power of deposit share, and none regarding the predicting power of equity.

Earnings management in banking: Dissecting the kink

This paper uses a distributional approach to explore earnings management for a sample of international banks including 27,585 bank-years observations between 1999-2013. Banks are often excluded from earnings management studies since several characteristics of this industry require a separate approach. Thus, various aspects of banks' earnings management remain largely unexplored. We start by investigating the existence of a smooth pre-managed earnings distribution and the presence of a kink in the distribution of various earnings measures down the income statement. We then analyse earnings streams happening between these two earnings measures in order to investigate what components of earnings contribute to the kink, and whether earnings management is behind the kink.

To our knowledge, the only study using a distributional approach to investigate earnings management in banking was conducted by Shen and Chih (2005). The authors used various statistical tests to analyse the presence of a kink around zero earnings. This irregularity was reported in previous studies of the nonfinancial industry. Shen and Chih (2005) confirmed the presence of a kink, and interpreted this kink as evidence of earnings management without conducting any further analysis. In addition, they did not explore the presence of a smooth pre-managed earnings distribution, nor did they analyse earnings streams in order to investigate whether earnings management was behind the kink. To our knowledge, only Dechow et al. (2003) investigated these topics, but for the nonfinancial industry.

In order to assess the presence of an irregularity around zero earnings as well as the magnitude of this irregularity, we rely on graphical evidence by plotting histogram of various earnings measures of the income statement. To formally assess the results, we use three statistical tests used in studies of the empirical literature. To assess whether earnings management is responsible for the kink, we compare earnings streams from banks in different earnings groups (negative earnings, small earnings, higher earnings). Again, we rely on graphical evidence and on a formal test to assess the significance of the results.

Our main findings are as follows. First, we show the existence of a smooth, pre-managed earnings distribution (Pre-impairment operating profit) in the banking industry, thus echoing findings from Dechow et al. (2003) for the nonfinancial industry. We further show that the distribution of Net income is characterised by a kink around zero earnings. In order to examine which components contribute to the kink, we examine different earnings streams that occur between these two earnings measures. We show that the distribution of Net income is asymmetrically shifted to the left relative to the distribution of Pre-impairment operating profit, and this shift causes the kink. This shift affects mostly banks with positive earnings. More specifically, banks with relatively high pre-managed earnings are disproportionally shifted to the left compared to banks with smaller positive earnings. This partial shift reflects higher earnings streams among banks with higher pre-managed earnings, i.e. earnings streams reducing more heavily reported earnings. This finding is compatible with a loss avoidance story predicting that firms manage earnings in order to report profits, even small ones. Compared to banks with higher pre-managed earnings that can afford stronger hits, banks with modest earnings are more likely to understate subsequent earnings streams to avoid reporting losses. This difference in earnings streams among these two earnings categories gives rise to an accumulation of observations in the small earnings area causing the kink.

The decomposition of total earnings stream shows that banks with higher pre-managed earnings have on average (1) higher impairment charges on loans, securities, and other credits as well as (2) higher tax expenses relative to smaller earnings banks. We show that both earnings streams are responsible for the apparition of the kink and its subsequent reinforcement. In the light of these results, earnings management appears to be an explanation for the kink, but only a partial one. The use of impairment charges for earnings management purposes is well-known and has been largely documented in the banking literature. Thus, the difference in terms of impairment charges among earnings groups is likely to reflect at least some degree of earnings management. It is, however, less likely that earnings management is the main driver behind the kinking effect of taxation. Given that tax expenses are largely a positive function of earnings, the fact that banks with higher earnings have higher tax expenses can rationally be expected without an earnings management explanation. Thus, our results tend to indicate that earnings management is only a partial explanation for the kink. We conduct several robustness tests of our results, both for the different earnings management statistics and for the mean difference tests of earnings streams among different earnings groups. In these robustness tests, we consider sample splits according to geographical criteria, a different scaling of earnings, and the possibility that a banks' main activity can have an influence on the results. We also consider alternative measures for our statistical tests. Overall, these robustness tests largely confirm our main findings.

The existence of a kink in the distribution of reported earnings is often interpreted as evidence of earnings management without further investigation. Similarly, the magnitude of the kink is often used to gauge the degree of earnings management. Given our findings, this is not unproblematic. Our study suggests that tax expenses have a kinking effect without being an obvious target of earnings management practices. Thus, at least part of the kink is not caused by earnings management since other factors, tax expenses in our case, also contribute to this irregularity. Interpreting the presence of a kink around zero earnings as evidence of earnings management without further investigation therefore bears the risk of drawing wrong conclusions.

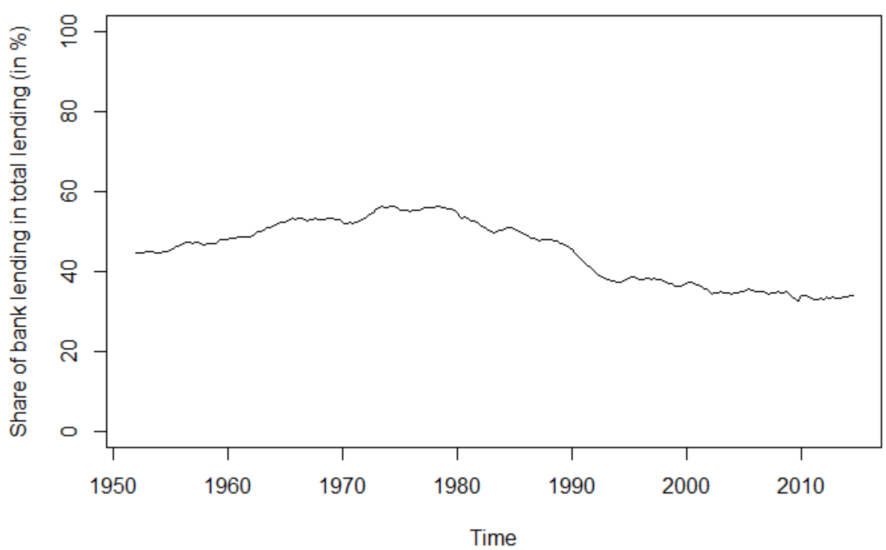
Shadow banking

Finally, I would like to conclude this thesis with some thoughts on shadow banking. While this thesis was dedicated to the traditional banking system, several activities traditionally carried out by banks tend to be increasingly fulfilled within the shadow banking system.

The International Monetary Fund (2014, p. 65) defines shadow banking as *"... financial intermediaries or activities involved in credit intermediation outside the regular banking system, and therefore lacking a formal safety net"*, while Shiller (2012, p. 43) defines shadow banks as *"...merely* *financial institutions that manage to escape banking regulation by designing themselves so that they do not fit the definition of commercial banks. They do not literally accept deposits, but instead get the money they lend in slightly different ways."* Examples of shadow banks include the now-failed Bear Stearns and Lehman Brothers. Shadow banks typically obtain commercial securitised loans or mortgages and enter into repurchase agreements with institutional investors, using the securities as collateral. That business creates liquid investments for institutional investors, which resemble deposits, and so the shadow bankers are in effect creating money as well. Thus, their activities may involve a risk of collapse of the entire economic system, just as with commercial banks (Shiller, 2012).[5]

In the past few decades, an upward trend in the size of shadow banking has been observed. As a result, shadow banking now constitutes a non-negligible fraction of total financial intermediation in many developing as well as emerging countries (see Figure 5.1 and Table 5.1 as illustrations of the importance of shadow banking in the U.S.).

Figure 5.1: Bank lending to the private non-financial sector, U.S. 1952-2013



Source of the data: Banks for International Settlements

[5]Another example is the structured investment vehicle (SIV), which was created by commercial banks before the financial crisis of 2007; they hoped to escape regulation by putting some of their business into the SIV's, which were considered separate (and unregulated) entities.

Table 5.1: Assets of financial institutions, U.S. 2002-2013

Year	Financial institutions		Central bank		Banks		Insurance companies		Pension funds		Public institutions		Other intermediaries	
	USD	% FI	USD	% FI	USD	% FI	USD	% FI	USD	% FI	USD	% FI	USD	% FI
2002	42,173	100.00	754	1.79	9,767	23.16	4,270	10.12	8,503	20.16	5,711	13.54	13,169	31.23
2003	46,546	100.00	797	1.71	10,570	22.71	4,832	10.38	9,337	20.06	6,141	13.19	14,869	31.94
2004	51,320	100.00	841	1.64	11,787	22.97	5,289	10.31	10,241	19.96	6,270	12.22	16,892	32.91
2005	55,655	100.00	879	1.58	12,806	23.01	5,597	10.06	10,942	19.66	6,370	11.45	19,061	34.25
2006	61,385	100.00	908	1.48	14,014	22.83	6,021	9.81	11,697	19.06	6,716	10.94	22,028	35.89
2007	67,526	100.00	951	1.41	15,362	22.75	6,336	9.38	12,292	18.20	7,640	11.31	24,945	36.94
2008	67,403	100.00	2,271	3.37	16,944	25.14	5,820	8.63	11,723	17.39	8,371	12.42	22,274	33.05
2009	68,451	100.00	2,267	3.31	16,936	24.74	6,204	9.06	12,717	18.58	8,425	12.31	21,902	32.00
2010	69,528	100.00	2,453	3.53	17,040	24.51	6,528	9.39	14,036	20.19	7,862	11.31	21,609	31.08
2011	71,143	100.00	2,947	4.14	17,948	25.23	6,717	9.44	14,377	20.21	7,785	10.94	21,369	30.04
2012	75,378	100.00	2,955	3.92	19,314	25.62	7,054	9.36	15,148	20.10	7,712	10.23	23,195	30.77
2013	81,269	100.00	4,074	5.01	20,204	24.86	7,508	9.24	16,350	20.12	7,931	9.76	25,203	31.01

Banks refer to the broader category of deposit-taking institutions and also include U.S. holding companies. Insurance companies include property-casualty insurers and life insurers. Pension funds' assets include the unfunded claims on the sponsor for private pension funds, state and local retirement funds, and federal retirement funds. Numbers are in USD billion. Source of the data: Financial Stability Board.

Traditional banks are adversely affected by these new competitors from shadow banking that do not face the same barriers of entry into banking and are not subject to the same regulatory constraints.[6] Thus, traditional banks may have felt the need to behave like shadow banks and to enter unconventional new lines or activities (e.g. originating subprime mortgage securities), ultimately creating risk for the entire economic system. While shadow banking has the potential to play a beneficial role for the economy by complementing traditional banking (e.g. by expanding access to credit or support market liquidity), the financial crisis of 2007-2008 has also revealed the threat that it can pose to overall economic activity (International Monetary Fund, 2014). It is therefore important for the sake of financial stability to understand and properly monitor shadow banking.

The academic literature about shadow banking, and particularly the empirical literature on this topic, is still in its nascent stage. Given the important size of shadow banking, this area could turn out to be one of the next promising field of research in finance. As noted by the International Monetary Fund (2014), the scarcity of data has so far substantially limited the scope of empirical studies. Given the need to better understand and monitor shadow banking because of its systematic riskiness (e.g. assessment of maturity mismatches, liquidity risks, interconnectedness with traditional banking), one can rationally expect that the necessary data will be collected. A first example is the recent release by the Bank for International Settlements of a database on credit to the private sector. In addition to the provision of credit by domestic banks covered by traditional domestic bank credit series, this database also includes debt held by the nonfinancial sector as well as cross-border lending (see Dembiermont, Drehmann, and Muksakunratana (2013) for more information on this database).

[6]New regulations, notably the Dodd-Frank Act in the United States, are designed to put many of these shadow banking activities under stronger regulation to help prevent a repeat of the crisis.

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Appendix A

Additional Tables from Study 1

Table 5.1: Regression results - Trimmed dependent variable

	1998-2002	2003-2006	2007-2009	2010-2013	1998-2002	2003-2006	2007-2009	2010-2013
	Asset-based measures				Income-based measures			
Type	−0.104***	−0.042**	−0.046**	−0.017	−0.143***	−0.055**	−0.062***	−0.025
	(0.01)	(0.05)	(0.05)	(0.37)	(0.00)	(0.02)	(0.01)	(0.25)
Diversity	−0.050**	0.006	0.021	−0.020*	−0.061***	−0.035**	−0.046***	−0.028**
	(0.01)	(0.67)	(0.18)	(0.10)	(0.01)	(0.02)	(0.00)	(0.02)
Deposit share	0.036	0.045**	0.043**	−0.021	0.048*	0.051***	0.051**	−0.019
	(0.21)	(0.01)	(0.05)	(0.29)	(0.08)	(0.01)	(0.02)	(0.31)
Wholesale share	0.030	0.047***	0.046**	−0.020	−0.002	0.034**	0.032	−0.020
	(0.22)	(0.00)	(0.03)	(0.20)	(0.94)	(0.04)	(0.15)	(0.18)
Operating profit	−0.034	0.009	0.059	0.056	−0.013	0.014	0.031	0.043
	(0.67)	(0.90)	(0.52)	(0.42)	(0.87)	(0.85)	(0.72)	(0.53)
Cost-to-income	0.004	−0.001	0.002	−0.070*	0.006	−0.003	0.002	−0.068*
	(0.52)	(0.92)	(0.52)	(0.09)	(0.29)	(0.76)	(0.49)	(0.09)
Loan loss provisions	0.622	2.719***	0.528**	0.474**	0.631	2.549***	0.513**	0.469**
	(0.29)	(0.00)	(0.03)	(0.03)	(0.25)	(0.00)	(0.04)	(0.03)
Z-Score	0.007**	−0.002	−0.003	0.002	0.007**	−0.001	−0.001	0.002
	(0.02)	(0.32)	(0.10)	(0.19)	(0.01)	(0.73)	(0.50)	(0.13)
Growth in assets	−0.012**	−0.003***	−0.001	0.000	−0.010**	−0.002**	0.000	0.000
	(0.01)	(0.01)	(0.33)	(1.00)	(0.02)	(0.02)	(0.82)	(0.92)
Log assets	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.84)	(0.87)	(0.92)	(0.80)	(0.32)	(0.88)	(0.77)	(0.72)
Equity	0.000	0.000**	0.000	0.000*	0.000	0.000*	0.000	0.000**
	(0.11)	(0.03)	(0.43)	(0.05)	(0.20)	(0.06)	(0.52)	(0.05)
Observations	3404	5144	4471	6571	3404	5144	4471	6571
R-squared	0.167	0.402	0.292	0.273	0.188	0.403	0.293	0.274
Macroeconomic control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regulatory control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Table 5.2: Regression results - Market-to-book value

	1998-2002	2003-2006	2007-2009	2010-2013	1998-2002	2003-2006	2007-2009	2010-2013
	Asset-based measures				Income-based measures			
Type	-1.291^{***}	-0.508^{***}	-0.666^{***}	-0.438^{***}	-1.547^{***}	-0.806^{***}	-0.634^{***}	-0.329^{***}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Diversity	-0.355^{*}	0.104	0.278^{**}	-0.201^{*}	-0.690^{***}	-0.423^{***}	-0.191^{*}	-0.045
	(0.08)	(0.42)	(0.01)	(0.05)	(0.00)	(0.00)	(0.08)	(0.62)
Deposit share	0.162	0.163	0.395^{**}	0.099	0.302	0.249	0.423^{***}	0.071
	(0.51)	(0.45)	(0.02)	(0.49)	(0.19)	(0.24)	(0.01)	(0.62)
Wholesale share	0.558^{**}	0.583^{***}	0.194	-0.131	0.182	0.388^{**}	0.045	-0.134
	(0.02)	(0.00)	(0.11)	(0.19)	(0.44)	(0.02)	(0.73)	(0.21)
Operating profit	7.756^{***}	16.918^{***}	5.738^{**}	1.959	7.536^{***}	14.559^{***}	5.584^{**}	1.870
	(0.00)	(0.00)	(0.01)	(0.11)	(0.00)	(0.00)	(0.02)	(0.12)
Cost-to-income	2.716^{*}	-0.115	0.295	1.052	1.353	-0.758	0.436	1.143
	(0.08)	(0.95)	(0.70)	(0.48)	(0.36)	(0.69)	(0.58)	(0.44)
Loan loss provisions	0.072	-0.242^{***}	0.047^{*}	-0.260	0.090^{***}	-0.264^{***}	0.047^{**}	-0.240
	(0.12)	(0.00)	(0.06)	(0.26)	(0.01)	(0.00)	(0.05)	(0.28)
Z-Score	-0.201^{***}	-0.038^{***}	-0.023^{***}	-0.002	-0.170^{***}	-0.033^{***}	-0.017^{**}	-0.002
	(0.00)	(0.00)	(0.00)	(0.39)	(0.00)	(0.01)	(0.03)	(0.38)
Growth in assets	1.260	1.710^{*}	0.228	2.472^{**}	0.868	1.227	0.237	2.578^{**}
	(0.24)	(0.07)	(0.78)	(0.04)	(0.42)	(0.17)	(0.79)	(0.03)
Log assets	0.158^{***}	0.027	-0.007	0.039^{***}	0.164^{***}	0.038^{**}	0.009	0.035^{**}
	(0.00)	(0.16)	(0.68)	(0.01)	(0.00)	(0.05)	(0.58)	(0.02)
Equity	-1.044	-3.977^{***}	-1.608^{***}	-0.045	-0.778	-3.924^{***}	-1.687^{***}	-0.061
	(0.16)	(0.00)	(0.00)	(0.89)	(0.26)	(0.00)	(0.00)	(0.85)
Observations	3421	5171	4490	6595	3421	5171	4490	6595
R-squared	0.279	0.269	0.297	0.217	0.296	0.273	0.289	0.216
Macroeconomic control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regulatory control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Table 5.3: Regression results - Reduced form regression

	1998-2002	2003-2006	2007-2009	2010-2013	1998-2002	2003-2006	2007-2009	2010-2013
	Asset-based measures				Income-based measures			
Type	-0.165^{**}	-0.052^{**}	-0.067^{**}	-0.018	-0.193^{***}	-0.060^{**}	-0.070^{***}	-0.016
	(0.01)	(0.03)	(0.02)	(0.42)	(0.00)	(0.01)	(0.01)	(0.49)
Diversity	-0.075^{**}	0.007	0.013	-0.023^{*}	-0.104^{***}	-0.050^{***}	-0.052^{***}	-0.022
	(0.03)	(0.71)	(0.47)	(0.10)	(0.00)	(0.00)	(0.00)	(0.13)
Operating profit	1.269	3.375^{***}	0.415	0.367	1.337^{*}	3.177^{***}	0.384	0.368
	(0.11)	(0.00)	(0.18)	(0.21)	(0.07)	(0.00)	(0.22)	(0.21)
Log assets	0.003	-0.006^{***}	-0.008^{***}	0.002^{*}	0.004	-0.004^{**}	-0.005^{**}	0.003^{*}
	(0.32)	(0.00)	(0.00)	(0.10)	(0.16)	(0.03)	(0.01)	(0.06)
Observations	3421	5171	4490	6595	3421	5171	4490	6595
R-squared	0.161	0.351	0.233	0.285	0.189	0.353	0.234	0.285
Macroeconomic control variables	No	No	No	No	No	No	No	No
Regulatory control variables	No	No	No	No	No	No	No	No
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Table 5.4: Regression results - IV: Activity restrictions

	1998-2002	2003-2006	2007-2009	2010-2013	1998-2002	2003-2006	2007-2009	2010-2013
	Asset-based measures				Income-based measures			
Type	−0.093**	−0.080***	−0.102***	−0.024	−0.134***	−0.135***	−0.091***	−0.029*
	(0.03)	(0.00)	(0.00)	(0.26)	(0.00)	(0.00)	(0.00)	(0.10)
Diversity	0.808*	9.203***	−0.037	−0.165	−0.246**	0.365***	−0.001	0.046
	(0.08)	(0.00)	(0.97)	(0.43)	(0.02)	(0.00)	(1.00)	(0.63)
Observations	3421	5171	4490	6595	3421	5171	4490	6595
R-squared	0.020	0.028	0.060	0.008	0.040	0.043	0.059	0.009
Macroeconomic control variables	No	No	No	No	No	No	No	No
Regulatory control variables	No	No	No	No	No	No	No	No
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Table 5.5: Regression results - IV: Diversification others

	1998-2002	2003-2006	2007-2009	2010-2013	1998-2002	2003-2006	2007-2009	2010-2013
	Asset-based measures				Income-based measures			
Type	−0.098**	−0.085***	−0.086***	−0.012	−0.139***	−0.127***	−0.058***	−0.007
	(0.04)	(0.00)	(0.00)	(0.60)	(0.00)	(0.00)	(0.01)	(0.71)
Diversity	−0.096	0.092	0.149***	0.133***	−0.105**	0.130***	0.200***	0.184***
	(0.39)	(0.18)	(0.00)	(0.00)	(0.03)	(0.01)	(0.00)	(0.00)
Observations	3421	5170	4478	6575	3421	5170	4478	6575
R-squared	0.019	0.018	0.067	0.015	0.039	0.042	0.079	0.026
Macroeconomic control variables	No	No	No	No	No	No	No	No
Regulatory control variables	No	No	No	No	No	No	No	No
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Table 5.6: Regression results - IV: Lagged diversification

	1998-2002	2003-2006	2007-2009	2010-2013	1998-2002	2003-2006	2007-2009	2010-2013
	Asset-based measures				Income-based measures			
Type	-0.085^{*}	-0.060^{***}	0.007	-0.019	-0.092^{**}	-0.113^{***}	-0.060^{***}	-0.018
	(0.05)	(0.00)	(0.66)	(0.20)	(0.02)	(0.00)	(0.00)	(0.24)
Diversity	-0.181^{**}	-0.116^{***}	-0.057^{**}	-0.014	-0.202^{***}	-0.161^{***}	-0.072^{***}	-0.017
	(0.02)	(0.00)	(0.02)	(0.52)	(0.00)	(0.00)	(0.00)	(0.44)
Observations	3238	5129	4474	6555	3238	5129	4474	6555
R-squared	0.117	0.253	0.219	0.278	0.141	0.273	0.225	0.278
Macroeconomic control variables	No	No	No	No	No	No	No	No
Regulatory control variables	No	No	No	No	No	No	No	No
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank