Essays in credit risk, banking, and financial regulation

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Essays in Credit Risk, Banking, and Financial Regulation

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ESSAYS IN CREDIT RISK, BANKING, AND FINANCIAL REGULATION

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As the reader will notice, this dissertation is reflective of my broad affinity towards research on policy-relevant issues. This affinity has manifested itself throughout my

PhD, both in the choice of topics, as well as in the decision to pursue a number of visiting research positions at policy institutions and international organizations. My journey around policy institutions began at the Dutch Central Bank in Spring 2015, continued at the International Monetary Fund and the European Central Bank during the second half of 2015, and ended - in full circle - at the Dutch Central Bank in June 2016. Throughout the journey, I had the opportunity to work with and learn from many incredible people with highly diverse backgrounds. I will fondly remember this as the period that allowed me to broaden my horizons, make new friendships, and chart the course of my future aspirations.

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Amsterdam, August 2016

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List of Acronyms

AE Advanced Economies. xii, 1, 10, 11, 124, 128–130, 132, 144, 145, 147, 153–156

ASC Abnormal CDS Spread Change. xii, 33

AUC Area Under the ROC Curve. xii, 74, 75, 78–80

BCBS Basel Committee on Banking Supervision. xii

BIS Bank for International Settlements. xii, 126

CAMEL an acronym that relates to the dimensions of bank conditions assessed by the system, namely: **C**apital adequacy, **A**sset quality, **M**anagement quality, **E**arnings, and **L**iquidity. xii, 58–60, 66, 68, 69

CAP Capital Assistance Program. xii, 62

CASC Cumulative Abnormal CDS Spread Change. xii, 33, 34

CDS Credit Default Swap. vi, xii, 3, 4, 14, 16, 18, 19, 24, 29, 30, 32, 33, 51, 54

CEGR Cumulative Excess Growth Rates. xii, 135, 136, 143, 144

CET1 Core Equity Tier 1 Capital. xii, 97, 103, 107

CIASC Cumulative Industry Abnormal CDS Spread Change. xii, 33–35, 37

CRA Credit Rating Agency. xii, 2, 3

DTA Deferred Tax Assets. xii, 8, 94, 96, 98, 103, 104, 107, 114, 119, 120

DTI Debt-to-Income. xii, 125

EME Emerging Market Economies. xii, 10, 54, 124, 128–130, 132, 144, 145, 147, 153–156

ESRB European Systemic Risk Board. xii, 1, 165

EU European Union. xii, 1, 62, 71

EWS Early Warning Systems. xii, 8, 94, 107, 119

FDIC Federal Deposit Insurance Corporation. xii, 57, 61, 62, 70, 110

Fed The Federal Reserve System (the central banking system of the U.S.). xii, 3

GFC Global Financial Crisis. xii, 1–3, 5–9, 54, 94, 100, 103, 131, 146, 147

GICS Global Industry Classification Standard. xii, 30, 33, 40

GMPI Global Macroprudential Policy Instruments Database, IMF. xii, 128

IASC Industry Abnormal CDS Spread Change. xii, 33

IIIT Intra-Industry Informational Transfer. vi, vii, xi, xii, 4, 5, 14, 23–26, 33–35, 37, 39, 40, 45–51, 54

IMF International Monetary Fund. xii, 124, 126, 128, 130

IRB Internal Rating-Based Approach (Basel). xii, 8, 9, 94–97, 100, 102, 103, 106–108, 110, 113–120

LCR Liquidity Coverage Ratio. xii

LGD loss-given-default. xii, 100

LR Leverage Ratio. x–xii, 8, 9, 94, 95, 97, 99–103, 107, 110, 114–121

LTV Loan-to-Value. xii, 10, 123–125, 128, 149

MaP Macroprudential Policy. viii, xi, xii, 2, 3, 9–11, 123, 124, 128–135, 143–147, 153–156

MBS Mortgage-Backed Security. xii, 3

NSFR Net Stable Funding Ratio. xii

PD probability of default. xii, 95, 100

ROC Receiver operating characteristic. xii, 74, 75, 80

RW Basel risk weights. x–xii, 8, 9, 94–96, 101–103, 107, 110, 113–120

RWA Risk-Weighted Assets. xii, 9, 69, 82, 85, 89, 94, 95, 97–99, 102, 120, 121

RWCR Risk-Weighted Capital Ratio. xii, 8, 9, 94, 95, 97, 99, 101–103, 108, 110, 114–120

S&P Standard & Poor's. xii, 4, 5, 14–18, 25, 26, 29, 32–35, 37, 46, 51, 54

SA Standardized Approach. xii, 8, 95–97, 107

SIFI Systemically Important Financial Insititutions. xii, 8, 94

TARP The Troubled Asset Relief Program. xii, 62, 74, 78

WEO World Economic Outlook, IMF. xii, 126, 130

CHAPTER 1

Introduction

The adverse dynamics in the U.S. mortgage market, which began to gather pace during early 2007, culminated in the failure of Lehman Brothers – a U.S. investment bank – on September 15, 2008. The bankruptcy sent shockwaves across the global financial system, with the spillovers being particularly acute in the Advanced Economies (AE) in Europe and in Asia. The event, unprecedented in its international dimension[1] and scale, gave birth to what is now commonly referred to as the Global Financial Crisis (GFC).

The GFC exposed serious flaws in the global financial system architecture and regulation. It raised questions about its causes, remedies, and long-term consequences. It also pushed the economic profession to rethink concepts and ideas, that had hitherto constituted the mainstream economic thinking. The impetus has manifested in discussions that have permeated academic, regulatory, and practitioner circles for many years to come. It produced several keystone pieces of banking regulation, both at the national level (e.g. Dodd-Frank Wall Street Reform and Consumer Protection Act in the U.S., Vickers report in the U.K., Liikanen report in the European Union (EU)), and internationally (Basel III). It also generated sweeping institutional reforms, giving rise to institutions with new types of mandates tied to addressing market failures highlighted by the crisis. One such example is establishment of the European Systemic Risk Board (ESRB) on 16 December 2010, with a goal to monitor, prevent and mitigate systemic risks in the European Union member countries.

[1] In contrast to the previous banking crises that were typically limited to specific countries or regions, the GFC generated unprecedented levels of cross-country contagion, especially within the group of AE.

This thesis aims to contribute to several important and, at times, heated debates that have captured interest of academics and policy makers after the GFC. It is structured as a collection of four independent empirical essays, which revolve around two overarching themes. These are: (1) the quality of information production in financial markets (Chapters 1-3) and (2) the motivations and consequences of the financial sector policies and regulations deployed in response to the GFC (Chapters 3-4).

The first main leitmotif in this thesis concerns the quality of information production in the financial markets. Information asymmetry between savers and the users of funds is one of the key deviations from the perfect capital market assumptions in the real-life financial markets. Since the users of funds are typically better informed and have more control over the quality of their investment projects than lenders or investors, the latter may be reluctant to disburse funds due to the possibility of financing an intrinsically bad project - a lemon (Akerlof, 1995), or for a fear of being expropriated by opportunistic actions of a borrower once the project has already been financed (Arrow, 1968).

Modern financial markets feature at least two broad means of reducing information asymmetry between savers and entrepreneurs. The first involves delegation of information production and monitoring to information intermediaries, such as credit rating agencies and financial analysts, whose role is to learn about the hidden information about the borrower (Healy and Palepu, 2001). The second remedy consists of the voluntary and regulated disclosure of private information by borrowers directly to investors, typically in the form of periodic financial reports.

The GFC raised many questions about the quality of information production in the financial markets, some of which are addressed in this thesis. Examples of the questions, which we examine in the following chapters include: How informative are signals produced by the information intermediaries, such as the Credit Rating Agencies (CRAs) (Chapter 2)? Do rating signals trigger information spillovers beyond the rated entities, and if so, what is driving such spillovers (Chapter 2)? How informative were bank accounting disclosures in identifying banks that failed during the GFC (Chapter 3)? How does the information content of bank accounting disclosures vary across countries and to what extent can these variations be explained by domestic disclosure regulations (Chapter 3)? Are rules-based reporting regimes more conducive to accurate reporting by banks than discretion-based regimes or vice versa (Chapters 3 and 4)?

The second overarching theme in this thesis concerns the motivations and consequences of specific banking sector policies and regulations deployed in response to the GFC. Authorities responded to the crisis with two broad types of banking sector measures. The first consists of crisis management measures, aimed at mitigating market turmoil and restoring confidence in the banking system. This category of policy responses comprises of measures such as (1) deposit guarantees, (2) debt guarantees, (3) capital assistance measures, (4) credit market interventions, and (5) asset relief measures.

The second set of measures consists of policies that are aimed at improving resilience of the financial system to future shocks. These policies fall into two groups: (1) micro-prudential and (2) macro-prudential. The focus of micro-prudential supervision is to limit distress of individual financial institutions. On the other hand, macro-prudential policies (MaPs) aim to prevent financial system-wide distress[2].

The increase in bank regulation after the GFC, accompanied with unprecedented expansion of mandates of the monetary authorities and bank regulators, has raised many questions about the motivations behind and the consequences of the new policies. This thesis addresses some of these questions. Specifically, it aims to shed light on the following issues: To what extent do Basel-based regulatory capital ratios reported by banks proxy the true economic capital in their balance sheets (Chapter 4)? Does discretion afforded by the internal rating-based modeling approaches under Basel impair the information content of bank risk weights (Chapter 4)? Do banks strategically report their regulatory capital ratios (Chapter 4)? To what extent do macro-prudential measures achieve the goal of managing the credit cycle, and are they subject to regulatory arbitrage (Chapter 5)?

The thesis is structured as a collection of four independent essays. Chapter 2 examines information content of credit ratings, and tests for the presence of spillovers of rating information across industries. The chapter is based on Cizel (2013), published in the Autumn 2013 volume of the *Journal of Fixed Income*. Chapter 3 is based on Cizel, Altman, and Rijken (2014) and studies bank distress in Western European countries and the U.S. during the GFC. It also examines the nexus between information content of bank accounting fundamentals, and bank reporting discretion across countries. Chapter 4 is based on Cizel and Rijken (2016) and uses the empirical framework and the dataset developed in Chapter 3 to test some of the underlying assumptions behind the Basel III bank capital regulation. Finally, Chapter 5, based on Cizel, Frost, Houben, and Wierts (2016) and published as a peer-reviewed IMF Working Paper - studies the intended and unintended consequences of

[2] See Galati and Moessner, 2013 for an extensive comparison of the two sets of policies.

macroprudential policies (MaPs).

Chapters 2, 3 and 5 can be read independently and in any order. Prior to reading Chapter 4 the reader in advised to review Chapter 3, which provides a detailed explanation of our original dataset and the methodology. The remainder of this chapter provides brief summaries of each of the subsequent chapters.

Chapter 2: Transmission of Credit Rating Information across Industries in CDS Markets

Motivation. Chapter 2 focuses on the role of Credit Rating Agencies (CRAs). Credit ratings are ubiquitous in financial markets. They are often seen as one of the key devices to mitigate information asymmetry between investors and corporate or sovereign entities that aspire to raise finance by tapping the markets. In fact, possession of a credit rating assigned by a nationally recognized CRA is often a precondition for public issuance of bonds or equity by an entity.

The commonly accepted narrative on the causes behind the GFC sees CRAs as at least partially culpable for the crisis (e.g., see Gorton and Metrick, 2012 and Caprio, 2013). To a large extent, this is due to their involvement in credit assessment - or rather, the lack thereof - of toxic mortgage-backed securities (MBS) in the run-up to the crisis. Ben Bernanke, chairman of the Fed at the time of the GFC, argued that the MBS debacle contributed to the loss of confidence in CRAs, which in turn produced an "information fog"[3], where market participants stopped relying on the assessments of CRAs in their investment decision. In the same vein, others have criticized CRAs' reliance on the "issuer pays" business model, arguing that the conflict of interest that is inherent in the model, further diminishes information value of CRAs' ratings. These criticisms converge in their implication that credit ratings contain relatively little useful information for assessing the prospects of the rated entities.

The information-based explanation for the existence of CRAs has been subject to an extensive academic research. The literature has mostly focused on estimating the impact of credit rating changes on the prices of rated companies' publicly traded securities (e.g. Pinches and Singleton, 1978, Griffin and Sanvicente, 1982, Goh and Ederington, 1993, Philippe et al., 2005, Konijn and Rijken, 2010). The main finding

[3]Bloomberg News (February 5, 2012): "Bernanke Voiced Alarm Over Credibility of Ratings Firms"

emerging from this literature is that credit ratings are informative in a sense that they precipitate an expected price reaction in the security prices of the companies that experience the rating event.

While the price relevance of credit rating information is already well established for the entities that experience a rating event, less is known about whether ratings also contain information that is price-relevant for entities beyond the one that experiences the rating event. Chapter 2, based on Cizel (2013), aims to fill this gap by studying information spillovers around credit rating changes. Specifically, the chapter examines the extent to which rating signals contain information that the market perceives to be informative about the future prospects of the industry in which a rated entity operates.

There are two key arguments on why a rating event of a given issuer may trigger price changes for other entities within the industry (see Lang and Stulz, 1992). The first is that such events can contain information about the prospects of an industry as a whole. According to this view, firms within the same industry are subject to imperfectly observable common factors and investors use any available signals to draw inference about these unobservables. The second explanation is that sector-wide price responses to the firm-specific events happen due to the investor overreaction (or panic) triggered by the event. Here, it is the irrational behavior on the part of investors that gives rise to the price contagion.

Chapter 2 studies the intra-industry informational transfers (IIIT), defined as the phenomenon whereby the firm-specific event of one firm in an industry can be used to make inference about the asset pricing distribution of the firm's industry-related peers. The key empirical implication underlying the IIIT is that, after controlling for confounding events, the price reaction of the rated company's industry peers around the rating event will be systematically different from zero. If the price response of industry is of the same direction as that of the event firm, the industry response is consistent with *"informational contagion"*, discussed and theoretically treated in Giesecke (2004) and Collin-Dufresne et al. (2010a). Alternatively, when the response of industry peers is of the opposite direction as the one of the event firm, the industry reaction is typically referred to as the *"competitive IIIT"* (see Lang and Stulz, 1992, Jorion and Zhang, 2007a), because such reaction may be justified by the setting, in which a signal of financial deterioration in one of the market players may be a good news for its competitors, since they may expect to benefit from increased monopolistic rents, if the event-firm were to go bust.

Methodology. We study the IIIT induced by rating signals in the context of the markets for corporate credit risk. In particular, we study the intra-industry CDS spread responses to credit rating announcements made by Standard & Poor's (S&P), Moody's, and Fitch between January 2003 and March 2011. The CDS dataset consists of about 900,000 daily observations covering the period between January 1, 2003, and March 31, 2011, and contains more than 400 U.S. corporate and financial reference entities. We merge the CDS dataset with the equity price data from CRSP, and with the accounting data from Compustat for the cross-sectional analysis. Credit rating announcements for the corresponding period are obtained from Bloomberg. The announcements come from the three major rating companies: S&P, Moody's, and Fitch, and consist of four types of rating events: rating downgrades, rating upgrades, negative rating reviews, and positive rating reviews. We study the announcement effects using a variant of event study methodology, which is adapted to the analysis of CDS spreads.

Key Results. We find statistically and economically significant industry spread responses to the announcements made by S&P, and only marginally significant and insignificant industry spread responses to the rating signals of Moody's and Fitch, respectively. This suggests that S&P announcements contain the largest component of the industry-wide information. In the case of S&P, we observe strong evidence in favor of contagious IIIT, implying that on the day of announcement the industry abnormal spreads tend to move in the same direction as the event-firm spreads. This finding holds across all four types of rating events, and in particular for the cases in which the event-firm spread reaction has its predicted sign (positive (negative) spread change in the case of negative (positive) rating news). The magnitude of the industry peer reaction (to S&P announcements) is found to be about 6% of the event-firm abnormal spread change. Stratification and multivariate regression analyses reveal a rich pattern of IIIT behavior across several event-firm, event, and industry characteristics. For negative rating events, contagious IIIT effects tend to be stronger when event-companies: (a) are relatively large (only in the case of downgrades), (b) come from industries with large industry peers, (c) have high degree of cash-flow similarity with their industry peers, (d) are highly leveraged, (e) have higher than industry-average credit rating before the event, and (f) come from relatively credit-worthy industries. For positive rating events, the contagious IIIT effects tend to increase with: (a) industry-peer cash flow similarity, and (b) degree of financial distress, characterized by below-average event-firm credit quality and low average industry credit quality. These results contribute to our understanding of credit risk correlations, and are consistent with recent theoretical models of credit risk correlations of Giesecke (2004) and Collin-Dufresne et al. (2010a)

Chapter 3: The Information Content of Bank Accounting Fundamentals

Motivation. Chapter 3 examines the *quality of bank disclosure*. This is another issue that has featured prominently in the policy discussion since the onset of the GFC.

The prevailing view on the regulation of banks' public disclosures, enshrined in the Pillar 3 of Basel regulation, is that high quality disclosure contributes to ensuring financial stability, because it enhances market discipline. Public disclosure is expected to facilitate assessment of banks' financial condition by other market participants, including investors, other banks, regulators, and rating agencies, who can use this information to make their own risk assessment of the reporting banks' financial situation. Market discipline is then expected to operate via rewarding prudent and punishing imprudent institutions by affecting their cost of and access to capital and funding.

Bank public disclosure is informative to the extent to which (1) it captures the fundamental financial condition of the reporting bank, and (2) is consistent across institutions and over time. Consistency assures that market participants can use disclosure to assess the financial situation of banks in relation to peers, and track developments in their financial condition over time. Achieving consistency calls for a relatively rigid rule-based disclosure. Yet, such "straightjacket" approach may compromise the information content of disclosure by failing to capture intricacies of banks' individual business models and situations, which can only be accommodated by more discretionary reporting mechanisms.

With the implementation of Basel II, which began taking place just before the GFC, the emphasis within the rules-versus-discretion trade-off has shifted towards granting banks more discretion. This is especially the case for banks that follow the internal rating-based approaches for computing their regulatory capital. The level of discretion allowed by the framework reignited concerns about the consistency of information produced by banks, especially for their computation of risk-weighted assets. The debate has spun off a growing theoretical and empirical literature, which examines the ways in which banks may inadvertently or strategically use discretion, and, in the process, make their disclosure more opaque and less informative to the investors.

A growing number of regulatory reports and academic studies has recently questioned the comparability and risk-sensitivity of bank accounting disclosure during the GFC (see Mariathasan and Merrouche, 2014; BCBS, 2013; Le Lesle and Avramova, 2012). The main concern common to these studies is that a substantial accounting discretion of banks[4] may have contributed to systematic reporting biases by weak institutions and thus compromised the comparability of reported accounting signals between banks and across countries.

Chapter 3 contributes to this debate by examining the nexus between reporting discretion and the information content of banks' public disclosures. It does so by: (1) providing a comprehensive cross-country analysis of the information content of accounting fundamentals in anticipating bank distress in Western Europe and the U.S. during the period 2007-12, and (2) by studying the extent to which cross-country variations in (1) are explained by national bank disclosure requirements and their enforcement.

Methodology. To set the stage, we construct a comprehensive original database of bank distress events, drawing on a number of publicly available sources. The range of events covered by our database includes bank liquidations, bankruptcies, regulatory receiverships, distressed mergers, distressed dissolutions, and open-bank assistance, typically in the form of government recapitalization of ailing banks. We categorize events into two broad groups of bank resolution: (1) *bank closures*, corresponding to resolutions in which distressed banks cease to exist as independent entities, and (2) *open-bank resolutions*, in which banks are allowed to continue operating with the assistance of a government bail-out.

We analyze the drivers of bank distress by modelling the two competing groups of distressed bank resolutions in a logistic regression framework. In our benchmark specifications we test for a number of bank-specific variables, including size, regulatory capital, asset quality, liquidity, franchise, or charter value. Next, we conduct an

[4] With the implementation of Basel II, the emphasis within the rules-versus-discretion trade-off has shifted towards granting banks more discretion. This is especially true for banks that follow the internal rating-based approaches in computation of their regulatory capital. The level of discretion afforded by the framework re-ignited concerns about the consistency of information produced by banks, especially in regard with their computation of risk-weighted assets. The debate has spun off a growing theoretical and empirical literature, which examines the ways in which banks may inadvertently or strategically use discretion, and in the process make their disclosure more opaque and less informative to the investors.

in-depth examination of the information content of the accounting fundamentals by studying the ability of accounting numbers (1) to identify distressed banks within individual countries, and (2) to explain the aggregate incidence of bank distress during 2007-10. The final part of the chapter examines the extent to which the observed cross-country variations in the informativeness of bank accounting are explained by differences in the national disclosure standards and their enforcement by the regulators.

Key Results. The estimation of the benchmark bank distress models indicates that both closures and open-bank resolutions tend to occur in severely undercapitalized banks with poor asset quality (measured by the reported risk-weighted assets and loan impairments), low charter values (proxied by the net-interest spread), and high funding costs. We show that predictions generated by accounting-based models display a substantial cross-country variation in the bank distress classification performance. We also demonstrate that the values of accounting fundamentals, aggregated at the country level during the pre-crisis years of 2006 and 2007, fail to explain the 2007-10 aggregate incidence of bank distress across countries. Finally, we show that the informativeness of accounting fundamentals in the cross section of banks in a given country-year positively correlates with the quality of accounting standards and the stringency of their enforcement. In particular, accounting signals of bank distress tend to be stronger in countries with strong disclosure laws or with more stringent enforcement of the existing laws. We also demonstrate that the disclosure-quality/informativeness nexus holds when looking at the time series movements in accounting fundamentals at the level of distressed banks prior to the distress event.

Given that investors and regulators typically learn about banks' financial condition from the banks' public disclosures, our results have clear implications for bank disclosure regulation. The evidence in this chapter supports the oft-voiced concern that excessive flexibility in financial reporting undermines the ability of accounting signals to accurately capture the underlying financial health of banks. Obliqueness of accounting signals from distressed banks makes such information less useful for investors and regulators, and thus has negative regulatory implication. Perhaps the main implication of this conclusion is that the information content of accounting fundamentals, at least with respect to the identification of distressed banks, may be improved by increased stringency of bank disclosure laws and their enforcement.

The findings in this chapter also highlight the fact that bank disclosure regulations display substantial country-specific idiosyncratic elements despite the general trend towards global convergence of accounting standards (Camfferman and Zeff, 2015; Camfferman and Zeff, 2007).

Chapter 4: Assessing Basel III Capital Ratios: Do Risk Weights Matter?

Motivation. Another set of discussions that has attracted a lot of attention since the GFC, both academically and in the applied domain, concerns the quality of regulatory responses to the GFC. The merits of Basel III regulation have undoubtedly been one of the focal issues in this domain.

The Basel III agreements (see BCBS, 2008, 2010, 2011) are designed to address the inadequacies of the existing Basel II framework, exposed by the widespread financial turmoil following the financial meltdown in 2008. The prevailing view underlying the changes in Basel regulation is that the recent financial disruptions in the Western banking systems stem from the interplay of the following major factors: (1) insufficient capitalization - both in terms of quantity and quality of capital - that failed to capture the build-up of on-and-off-balance sheet risks, (2) excessive maturity mismatch, driven by bank funding structures biased towards short-term funding sources, and (3) insufficient holding of high quality liquid assets that would allow financial institutions to independenty cope with short-term funding squeezes, and (4) materialization of unforeseen systemic risks.

The Basel III agreement attempts to address these shortcomings by updating the existing capital regulation, as well as by introducing minimum liquidity standards, a hitherto uncharted territory in the previous Basel accords. With respect to the capital regulation, it aims to increase the quantity and quality of bank capital buffers by: (1) raising the minimum level of core Tier 1 equity capital, (2) introducing an additional capital conversion buffer and a countercyclical buffer, (3) increasing the quality of the capital base by requiring intangible assets such goodwill and deferred taxes to be deducted from regulatory capital, and (4) improving risk coverage by proposing a stronger capital treatment of securitisation and trading book exposures, as well as by stipulating more stringent requirements pertaining to counterparty credit risk. It also aims to improve systemic resilience by introducing a macroprudential leverage ratio (LR) requirement (ESRB, 2016; ESRB, 2015) and additional capital requirements for Systemically Important Financial Insititutions (SIFI).

While the motivations behind the changes in Basel III are widely accepted, many of its underlying premises have not been tested empirically. This is the gap that this chapter aims to fill. Specifically, it focuses on the capital-related initiatives of Basel III and empirically examines three sets of assumptions that are implicit Basel III capital regulation: (1) distress-relevance of bank regulatory capital, (2) poor loss-absorption properties of intangibles, such as deferred tax assets (DTAs) and goodwill, and (3) inclusion of risk-insensitive regulatory capital measures. Since each of these assumptions has empirical implications regarding the predictability of bank distress, we use the Early Warning Systems (EWS) framework for banks developed in Chapter 3 to test their validity. Specifically, we construct a series of tests that study the extent to which Basel III oriented measures explain distress events in a panel of Western European and the US banks around the GFC.

Methodology. Since each of the above assumptions has empirical implications regarding the predictability of bank distress, the EWS framework for banks developed in Chapter 3 lends itself as particularly suitable to test their validity. To test hypotheses underlying the new Basel regulation, we construct a number of measures that directly or indirectly relate to the regulation implemented in Basel III and test their association with bank distress in different subsamples of banks. Specifically:

- We test the distress-relevance of bank regulatory capital by examining the association between bank distress and various measures of bank capital, such as the leverage ratio (LR) and Risk-Weighted Capital Ratio (RWCR).
- We assess the value added of risk-sensitive capital regulation by studying the correspondence between distress and Basel risk weights (RW), after conditioning for the risk-insensitive capital measures (i.e. LR).

We propose a new rule of thumb, based on bank size, to distinguish between the IRB and non-IRB banks. By exploiting the novel source of information on the capital calculation approach of banks covered in the *SNL Financial* database, we show that the sample size split at US$ 10 billion serves a good discriminatory feature to distinguish between banks that follow the IRB or standardized approach (SA) in calculating their regulatory capital. Specifically, banks larger than $10 billion predominantly apply the IRB approach, whereas the ones below the threshold in majority opt for the SA approach.

The distinction between the IRB and non-IRB banks allows us to examine the extent to which the flexibility under the IRB approach affects the information content of bank risk-weighted capital ratios.

Results. Our key finding is on the information value of RWs[5] in the context of predicting bank distress. Specifically, we show that the association between RWs and bank distress is significant only in the subset of the non-IRB banks, while it is statistically insignificant for the IRB banks. This finding is consistent with a concern that the IRB banks may apply discretion in ways that hamper the association between their *reported* and real risks.

We provide further evidence in support of this explanation by showing that in response to the negative capital shocks, RWs of large (IRB) banks tend to fall, thus mitigating the effect of the shock on the banks' risk-weighted capital ratio (RWCR). We show that the downward movement in RWs attenuates the effect of a capital shock on the IRB bank's RWCR by 0.3pp for each 1pp fall in bank capital. In contrast, we show that for the small (non-IRB banks), which have less discretion in reporting their RWs, the relationship between the negative capital shocks and RW is significantly weaker or disappears.

The evidence presented in this chapter highlights the discrepancy between banks' *reported* capital and its economic (conceptual) counterpart, especially in the case of the large (IRB) banks. This confirms the concerns that have led to the recent regulatory push towards (1) improving the quality composition of regulatory capital and (2) increasing reliance on *risk-insensitive* measurement of bank capital, encapsulated in the LR. While the introduction of the minimum LR requirements represents one of the major moves towards less risk sensitive capital requirements in the Basel III, the authorities are currently considering a variety of additional measures, whose aim is to limit bank discretion in the use of the RWs. This includes the introduction of RWA floors on several types of exposures, such as residential mortgages, to which banks typically assign relatively low risk weights.[6] While the evidence in this chapter provides some support for these initiatives, further research is needed to examine other potential consequences of their introduction.

[5]In line with the literature (e.g. Mariathasan and Merrouche, 2014; Le Lesle and Avramova, 2012), Basel RWs are defined as the ratio between risk-weighted assets (Risk-Weighted Assets (RWA)) and the size of bank balance sheet.

[6]`http://zanders.eu/en/latest-insights/why-dutch-banks-fear-basels-new-capital-floor/`

Chapter 5: Intended and Unintended Consequences of Macroprudential Policies

Motivation. There has been a remarkable surge in deployment of MaPs after the GFC. This was largely because the GFC highlights the importance of systemic risk externalities, where activities of individual market players influence outcomes of the financial system as a whole. One of the key lessons of the crisis is that systemic risk externalities need to be regulated in order to ensure the stability of the financial system. MaP policies are designed with precisely this aim in mind. They consist of a diverse set of instruments, that includes loan-to-value, and debt-to-income caps, various balance sheet concentration ratios, counter-cyclical capital buffers, and others. What all these instruments have in common is that they target some aspect of systemic risk externalities. For example, counter-cyclical capital buffers were put forward by Basel III to increase resilience against boom and boost periods in bank credit, and thus limit the adverse effects of excessive credit movements on the real economy.

One of the increasingly voiced concerns that has accompanied the expansion of MaPs is that they may be subject to regulatory arbitrage, with credit provision flowing from the sectors or countries with relatively tight regulation to the ones with more loose regimes. This phenomenon has been referred to by the literature as the "boundary problem" (Goodhart, 2008). Specifically, macroprudential policy may have the consequence of shifting activities and risks both to: (i) foreign entities (e.g. bank branches and cross-border lending) and (ii) non-bank entities (e.g. shadow banking, also referred to as market-based financing). Whereas several papers have estimated intended effects MaPs on variables such as credit growth and housing prices, and whether measures leak to foreign banks, cross-sector substitution effects have – to the best of our knowledge – not yet been tested empirically.

This chapter aims to fill this gap. It investigates whether MaPs lead to substitution from bank-based financial intermediation to non-bank intermediation. It does so by examining the behavior of bank and non-bank credit around the activation of MaPs, controlling for the counterfactual rate of credit growth (i.e. credit growth that would have prevailed in absence of MaP deployment).

Methodology. The chapter examines the effects of MaPs by studying the behavior of bank credit, non-bank credit, total credit, and net sectoral credit flows, before and after the implementation of MaPs. Including the timing of the effects is important given that market participants may react to measures that have been announced but that have not yet taken effect. Moreover, macroprudential authorities may respond to periods of high or low credit growth by tightening or easing MaPs. We therefore apply a leads-and-lags model (Atanasov and Black, 2016). This model is suitable for checking pre-treatment and post-treatment trends relative to control groups of entities (in our case countries). Pre-treatment trends that are statistically different from 0 may be indicative of endogeneity issues, since the occurrence of the event may then be explained by the abnormal movements in the dependent variable (in our case credit) during the pre-event period.

MaP events are defined as the year in which a country implements a macroprudential tool. To isolate the movements in credit flows that can be attributed to MaPs, we adjust the actual credit growth by a counterfactual rate of credit growth that would have prevailed in absence of a MaP. We then use event study methodology to examine the divergence between the resulting adjusted and actual growth rates around MaPs.

Results. Results confirm that MaPs reduce bank credit growth. In the 2 years after the implementation of MaPs, bank credit growth falls on average by 7.7 percentage points relative to the counterfactual of no measure. This effect is much stronger in Emerging Market Economies (EME) than in AE. Beyond this, the analysis indicates that quantity-based measures have much stronger effects on credit growth than price-based measures, both in advanced and emerging market economies. In cumulative terms, quantity measures suppress bank credit growth by 8.7 percentage points over 2 years relative to the counterfactual of no policy change. These results are in the same order of magnitude as those of Morgan et al. (2015), who find that economies with Loan-to-Value (LTV) polices (which we classify as a quantity constraint) have experienced residential mortgage loan growth of 6.7% per year, while non-LTV economies have experienced 14.6% per year. Moreover, for the effect on bank credit, our results have the same order of magnitude as those of Cerutti et al. (forthcoming), who find stronger effects in emerging market economies than in advanced economies, just as we do.

Our main contribution to the literature is in our findings on substitution effects: the effect of MaPs on bank credit is always substantially above the effect on total credit to the private sector. Whereas bank credit growth falls on average by 7.7 percentage points relative to the counterfactual of no measure, non-bank credit increases after the implementation of MaPs so that total credit falls by 4.9 percentage points on average. Next to this general result we find remarkable differences between country groups and instruments. First, substitution effects are stronger in AEs. This is in line with expectations given their more developed financial systems, with a larger role for market-based finance. Second, substitution effects are much stronger in the case of quantity restrictions, which are more constraining than price-based measures. Moreover, we find strong and statistically significant effects on specific forms on non-banking financial intermediation, such as investment fund assets.

CHAPTER 2

Are Credit Rating Announcements Contagious? Evidence on the Transmission of Information Across Industries in Credit Default Swap Markets[1]

2.1 Introduction

Information can be contagious. In financial markets, this premise has found both anecdotal and empirical support. With respect to the latter, there exists the evidence that firm-specific events can sometimes give rise to sector- or economy-wide price movements. A recent example of such event is the bankruptcy of Lehman Brothers, whose Chapter 11 filing on September 15, 2008, precipitated a widespread turmoil in the markets for all major financial assets. Another example is the accounting scandal of Enron in October 2001, which resulted in plunging equity prices and increased borrowing costs for a number of the company's industry peers.

The focus of this chapter is to investigate whether rating signals contain information that the market perceives to be informative about the future prospects of the

[1] This chapter is based on Cizel (2013), published in the Autumn 2013 volume of the Journal of Fixed Income. The post-scriptum at the end of this chapter outlines several new developments in this stream of literature that took place after the publication of the article.

industry in which a rated entity operates. While there exists an established body of literature that investigates the informational content of rating signals for companies that experience the rating events (e.g. Pinches and Singleton, 1978; Griffin and Sanvicente, 1982; Goh and Ederington, 1993; Philippe et al., 2005), little has been done to verify whether rating announcements contain information, relevant for other firms in the industry. This gap in literature highlights the need for more research on the industry-specific informational value of rating announcements.

Two alternative views have been suggested to rationalize the sector-wide asset-price reactions to the firm-specific events (see Lang and Stulz, 1992). First is that such events contain information about the prospects in the broader business environment. According to this view, investors in financial markets with asymmetric information use any available signals to re-update their beliefs about the future performance of assets. The second alternative is that sector-wide responses to the firm-specific events happen due to the investor overreaction (or panic) triggered by the event. Here, it is the irrational behavior on the part of investors that gives rise to the price contagion.

In this chapter, we investigate the intra-industry informational transfers (IIIT) induced by rating signals in the markets for corporate credit risk. In particular, we study the intra-industry CDS spread responses to credit rating announcements made by S&P, Moody's, and Fitch between January 2003 and March 2011. The CDS dataset consists of about 900,000 daily observations covering the period between January 1, 2003, and March 31, 2011, and contains more than 400 U.S. corporate and financial reference entities. We merge the CDS dataset with the equity price data from CRSP, and with the accounting data from Compustat for the cross-sectional analysis. Credit rating announcements for the corresponding period are obtained from Bloomberg. The announcements come from the three major rating companies: S&P, Moody's, and Fitch, and consist of four types of rating events: rating downgrades, rating upgrades, negative rating reviews, and positive rating reviews.

We find statistically and economically significant industry spread responses to the announcements made by S&P, and only marginally significant and insignificant industry spread responses to the rating signals of Moody's and Fitch, respectively. This suggests that S&P announcements contain the largest component of the industry-wide information. In the case of S&P, we observe strong evidence in favor of contagious IIIT, implying that on the day of announcement the industry abnormal spreads tend to move in the same direction as the event-firm spreads. This finding holds across all four types of rating events, and in particular for the cases in which the event-firm spread reaction has its predicted sign (positive (negative) spread change in the case of negative (positive) rating news). The magnitude of the industry peer reaction (to S&P announcements) is found to be about 6% of the event-firm abnormal spread change. Stratification and multivariate regression analyses reveal a rich pattern of IIIT behavior across several event-firm, event, and industry characteristics. For negative rating events, contagious IIIT effects tend to be stronger when event-companies: (a) are relatively large (only in the case of downgrades), (b) come from industries with large industry peers, (c) have high degree of cash-flow similarity with their industry peers, (d) are highly leveraged, (e) have higher than industry-average credit rating before the event, and (f) come from relatively credit-worthy industries. For positive rating events, the contagious IIIT effects tend to increase with: (a) industry-peer cash flow similarity, and (b) degree of financial distress, characterized by below-average event-firm credit quality and low average industry credit quality. These results contribute to our understanding of credit risk correlations, and are consistent with recent theoretical models of credit risk correlations of Giesecke (2004) and Collin-Dufresne et al. (2010a).

This chapter contributes to the existing market efficiency and informational transfer literature on the credit rating announcements in a number of ways. First, it represents the earliest attempt to investigate the industry credit spread responses to credit ratings events. Second, it features an extensive analysis of the cross-sectional determinants of industry responses to rating signals. The results of this analysis bear important implications for understanding the possible channels of intra-industry informational transfer. This, in turn, provides a helpful guide in constructing portfolios of credit-sensitive securities (see Jorion and Zhang (2007a) for the practical application of such knowledge). Third, the chapter provides the empirical evidence in favor of several recent theoretical models on credit risk correlations, e.g. Giesecke (2004) and Collin-Dufresne et al. (2010a). Developing an understanding of the informational contagion induced by rating changes has a direct application in the pricing of financial assets. If the informational contagion on the day of announcement exists, and the contagion effect is non-diversifiable, the rating announcement should represent a risk, that is priced by the investors. Given the interest in the pricing of credit risk (e.g., see Collin-Dufresne et al. (2010a) and Collin-Dufresne et al. (2010b)), the evidence presented in this chapter should provide a valuable source of validation of theoretical models in this area.

The structure of the chapter is as follows. Section 2.2 briefly describes the credit rating process. Section 2.3 provides the overview of the existing literature. Section

2.4 develops and provides explanations for the hypotheses tested later in the chapter. 2.5 describes the data and 2.6 describes the methodology. Section 2.7 reports the main empirical findings. Finally, Section 2.8 concludes.

2.2 Credit Rating Methodology

2.2.1 Rating Process

Rating agencies usually define their ratings as a variant of the following definition: "credit ratings are opinions about the ability and willingness of an issuer, such as a corporation, state or city government, to meet its financial obligations in accordance with the terms of those obligations (S&P, 2011)." The issuer, who wishes to be rated, usually first submits a request with an agency. During the pre-evaluation period the agency reviews the company's financial statements and forms a team of analysts that is responsible for the future surveillance of the company's creditworthiness. After the initial review of the publicly available information, the agency's analysts meet the firm's management, which typically provides additional (private) information that is needed for the analysts to form a rating opinion. Information gathered from the public files and evaluation meetings is next reported to the rating committee, which discusses the findings and votes for the final rating. Before the rating is published, it is usually communicated to the company, which is then allowed to appeal and present additional information, if it believes that the proposed rating mis-represents its underlying creditworthiness. After the first rating, the firm's performance is under a constant surveillance by a team of analysts, who also keep a regular contact with the firm's management.

A question, relevant for this chapter, is whether and why a rating change of a given issuer may be informative about the rated firm's industry prospects. One possible answer is that the assessment of industry prospects constitutes a major part of the rating evaluation. Indeed S&P (2011) reports that:

> /.../ the industry risk assessment goes a long way toward setting the upper limit on the rating to which any participant in the industry can aspire. Specifically, it would be hard to imagine assigning 'AA' and 'AAA' debt ratings or 'A-1+' commercial chapter ratings to companies with extensive participation in industries of above-average risk, regardless of how conservative their financial posture.

This suggests, that conditionally on the rating agencies possessing private information about the rated firms' industry prospects, one may expect to observe within-industry informational spillovers following the rating announcements. Rating agencies may possess such private information by the virtue of having an intimate knowledge of many firms within same industries, which, in turn, may allow them to be in a better position to predict the general industry movements.

2.2.2 Types of Rating Signals

Rating agencies signal their opinion about the relative creditworthiness of an entity by assigning it a rating from an alphanumeric scale[2]. When a rating agency believes that creditworthiness of an issuer has changed or is likely to change in future, they signal this to markets by rating changes (downgrades/upgrades), reviews for downgrade/upgrade[3], and rating outlooks (positive/negative).

Rating changes represent the most fundamental signal about the shift in rating agency's opinion of future prospects of an issuer's creditworthiness. Rating outlooks and rating reviews, on the other hand, are the opinions of the likely future changes in the creditworthiness of an issuer. The difference between rating outlooks and rating reviews is that the latter are intended to serve as relatively stronger indicator of the future path of issuer credit quality than the former. Konijn and Rijken (2010) provide support for this claim by finding that about one third of rating reviews results in the actual rating changes, compared with only one-tenth of correct "predictions" in the case of outlooks.

2.3 Previous Literature

2.3.1 Impact of Rating Changes on the Firm that Experiences the Event

The capital market literature on informational content of bond rating changes has traditionally focused at the pricing impact of rating announcements on firms that experience the bond rating event. This body of literature can be categorized into

[2]In the case of S&P and Fitch the rating scale from excellent to poor is AAA, AA+, AA, AA-, A+, A, A-, BBB+, BBB, BBB-, BB+, BB, BB-, B+, B, B-, CCC+, CCC, CCC-, CC, C, SD. For Moody's the rating scale is: Aaa, Aa1, Aa2, Aa3, A1, A2, A3, Baa1, Baa2, Baa3, Ba1, Ba2, Ba3, B1, B2, B3, Caa1, Caa2, Caa3, Ca, C.

[3]Also known as credit watches.

three major groups. The first group, initiated by the seminal chapter of Pinches and Singleton (1978), takes the perspective of the rated company's shareholders and investigates the impact of rating announcements on firms' equity. Motivated by the direct link between credit ratings and the creditworthiness of firms' debt, the second group of studies investigates the impact of credit rating announcements on prices of publicly traded debt (e.g. Katz (1974) and Grier and Katz (1976)). Beginning with Hull et al. (2004) and Norden and Weber (2004), researchers have also started to investigate the informational impact of rating changes on the credit default swap (CDS) spreads. In what follows we briefly outline the main findings and conclusions of these three groups of studies. In addition, Table 2.1 provides a condensed view of the ratings-based market efficiency research that has been done so far.

Equity Market

Pinches and Singleton (1978) and Griffin and Sanvicente (1982) are the earliest attempts to investigate the impact of rating announcements on the pricing of firms' equity. Their findings suggest that credit rating changes possess relatively little informational content. Using a sample of 207 Moody's rating changes, Pinches and Singleton (1978) report insignificant event window abnormal returns and conclude that rating changes are fully anticipated by the equity market. On the contrary, Griffin and Sanvicente (1982) find no anticipation effect but report a negative post-announcement drift following downgrades. Statistical power of the tests used in both studies is small, since they rely on monthly equity data, which might conceal the effect of rating changes on and around the day of announcement.

Subsequent literature, which relies on the daily equity data, finds several fairly robust properties in the stock behavior on and around rating announcement dates. First, studies like Glascock et al. (1987), Norden and Weber (2004), Konijn and Rijken (2010) report some degree of market anticipation of negative rating events [4]. Negative rating reviews and negative watch-listings appear to be more informative than the actual rating downgrades since they tend to precipitate stronger negative market response on the day of event and display lower degree of market anticipation (e.g, see Hand et al., 1992; Followill and Martell, 1997; Norden and Weber, 2004; Konijn and Rijken, 2010). Second, several studies report that the equity response to negative and positive announcements is asymmetric in a sense that negative announcements tend to precipitate stronger equity reaction than the positive rating news. Several

[4] In particular, they report significantly negative abnormal equity returns already months before the actual downgrades

explanations for this phenomenon have been proposed in the literature. Ederington and Goh (1998) conjecture that companies are more likely to publicly disclose good information than bad information, and that this makes positive information more anticipated by the markets. Jorion and Zhang (2007b), on the other hand, provide a theoretical framework and empirical evidence, which suggests that the asymmetric effect largely disappears when one conditions the equity response on the rating of the underlying company before the announcement takes place. Finally, several authors (e.g., Glascock et al., 1987) report reversals in abnormal equity returns after downgrade announcements take place. Konijn and Rijken (2010) find that the positive abnormal equity returns in the post-announcement period occur when the agency ratings confirm the general point-in-time credit model tendencies.

Bond Market

Some of the earliest studies on the informational effects of bond rating changes were done using corporate bond prices. These represent a natural point of interest because rating announcements are linked directly to the creditworthiness of the underlying debt instruments of the issuing entities. Results of the early research on bond markets are mixed. While Katz (1974) and Grier and Katz (1976) find some evidence of post-announcement drift following rating downgrades, Weinstein (1977) reports that bond markets anticipate credit rating changes already 7 to 18 months before the actual events. Conflicting results of these studies can be to large extent attributed to the poor data quality.

First reasonably consistent findings in this line of research began to be reported during the 1990s. In their seminal chapter, Hand et al. (1992) find significant negative price responses around the S&P watchlist additions and downgrades, and positive bond price responses around the rating upgrades. Similar findings are reported by Wansley et al. (1992) and Hite and Warga (1997), who also find that the announcement effect of downgrades is stronger for speculative-grade than for investment-grade issuers, and that the bond price jumps are particularly large when an entity is downgraded over the investment/speculative grade boundary. Kliger and Sarig (2000) supplements these results by showing that highly leveraged firms display stronger announcement effects than their less leveraged peers. Majority of studies considered above find that the negative rating announcements are partially anticipated by investors. They also provide some evidence that bond prices tend to react asymmetrically with respect to positive and negative news. Generally, upgrades precipitate weaker market responses than the downgrades of the same number of notches. Studies like Steiner and Heinke (2001) also find that bond markets tend to over-react to the negative rating news and display pronounced reversal in the weeks following such news.

CDS Market

Literature that analyzes the rating announcement effects on credit spreads using the bond pricing data faces at least two potential problems. First is that bonds are a very heterogeneous and at times illiquid class of assets, which makes the yield spreads computed from their prices a rather inaccurate proxy of pure credit risk. In particular, studies such as Huang and Huang (2012) show that only a small fraction of bond yield spreads can be attributed to credit risk directly, the rest reflecting factors such as liquidity and tax-related considerations (e.g. Driessen, 2005). Second, several studies (e.g. Houweling and Vorst, 2002) find that bond markets lag Credit Default Swap markets in terms of incorporating new credit-related information, which makes CDS contracts a relatively more suitable asset for testing informational effects of various announcements on firm credit spreads.

For the reasons stated above, bond prices represent a relatively unsuitable medium for analyzing whether bond rating announcements contain valuable information on future prospects of the firm. The rapid growth of the credit derivatives market since the later half of 1990s has given rise to Credit Default Swaps, which are becoming an increasingly standardized means for hedging credit risk of several types of credit issuers.

Hull et al. (2004) are the first to use CDS spreads to analyze the informational content of credit ratings. They find that downgrading announcements are anticipated by the CDS market at least a month before the actual event. They find a significant announcement window abnormal CDS reaction to negative rating reviews, but note that also these events displays some degree of market anticipation. Norden and Weber (2004) complement these findings by analyzing a larger number of rating events. They use rating announcements of S&P, Moody's, and Fitch, which allows them to analyze whether the market reaction to the rating announcements depends on the underlying source of the announcement. They find that S&P and Moody's announcement are the most informative, while Fitch rating announcements usually exhibit statistically insignificant announcement window market reactions. In line with Hull et al. (2004) they report a stronger announcement effect for negative reviews than for the actual downgrades and show that both types of rating announcements are anticipated by the market long in advance. Most recently, Galil and Soffer (2011) replicate the Norden and Weber (2004) methodology, also using CDS data. In addition they investigate how the alternative event-window cleaning strategies affect the significance of the market reaction to rating changes. They find that the standard practice of excluding the simultaneous rating events or the events that happen within a certain event window, underestimates the announcement effect of rating changes. The reason behind this is that simultaneous rating events tend to happen in economically more important times and excluding such events leaves one with the sample of economically unimportant events. They conclude that the findings of Hull et al. (2004) and Norden and Weber (2004) may underestimate the actual informational content of credit ratings.

2.3.2 Spillover Effect of the Credit Rating Changes

The preceding section testifies about the continuing academic interest in the informational effect of rating announcements for the companies that experience the rating event. Alternatively, one may ask whether rating events contain information that can be used to assess the creditworthiness of the firms within the industry of the rated company. First to attempt to answer this question in the contest of credit ratings are Akhigbe, Madura, and Whyte (1997), who analyze equity responses to rating announcements for both event firms as well as their industry peers. In line with previous literature they find that downgrades precipitate a negative reaction of the event firm's abnormal returns. They also report that this negative information spreads within the event firm's industry, but only under the condition that the event firm experiences a negative equity reaction. Jorion and Zhang (2010) replicate this study, but using a larger sample of rating events. They find that the direction of the information transfer following the negative announcements crucially depends on the initial rating of the event company. The net contagion effects are found to occur only when the event companies have investment-grade status. Ismailescu and Kazemi (2010) are the first and the only ones so far to attempt to investigate the informational transfer effects in the CDS market. They do so with the CDS on sovereign reference entities and find some evidence for the spillover of rating information across CDS of different countries.

Table 2.1 – Market Efficiency Literature on Bond Rating Changes

Authors	Market	Rating Event Data	Findings
Panel A: Event-Firm Reactions to Rating Signals			
Grier and Katz (1976)	Bond	S&P: 32 downgrades	Anticipation of rating changes evident for industrial bonds, not for public utilities. The magnitude of price reaction to adverse news is positively related to the maturity of the bond.
Weinstein (1977)	Bond	Moody's: 72 downgrades, 60 upgrades	Evidence of price change during 7 to 18 months before the rating event. No reaction during the 6 months prior the event or in the month of event.
Pinches and Singleton (1978)	Equity	Moody's: 69 downgrades, 111 upgrades.	No market reaction to downgrades/upgrades. Rating changes are fully anticipated.
Griffin and Sanvicente (1982)	Equity	S&P and Moody's: 94 downgrades, 86 upgrades.	Significantly negative reaction to downgrades. No reaction upgrades.
Wansley et al. (1992)	Equity	Moody's	Significantly negative reaction for firms, which are listed on S&P CreditWatch and are subsequently downgraded.
Holthausen and Leftwich (1986)	Equity	S&P and Moody's: 1014 rating changes	Downgrades across the rating classes associated with negative equity response. No response for downgrades within rating classes. No effect for upgrades.
Zaima and McCarthy (1988)	Equity	Moody's	Negative reaction to downgrades, no reaction to upgrades.
Hand et al. (1992)	Equity/Bond	S&P and Moody's: 1100 rating changes	Equity: Downgrades among speculative grade bonds result in a stronger market reaction. Stock markets react only to downgrades and negative watchlist additions. No equity response to upgrades. Bond: Significant abnormal bond returns observed on the unanticipated S&P's watchlist additions. Significant event window price effects also observed for actual downgrades and upgrades.
Goh and Ederington (1993)	Equity	Moody's: 243 downgrades,185 upgrades	Positive reaction to downgrades for firms, whose downgrade results from the increase in leverage. Downgrades that stem from the negative firm prospects result in a negative market reaction. Downgrades and upgrades are not homogenous groups, one should consider the underlying reasons for rating changes.

Table 2.1 continued on next page

Table 2.1 continued from previous page

Authors	**Market**	**Rating Event Data**	**Findings**
Hite and Warga (1997)	Bond	S&P and Moody's: 483 downgrades, 312 upgrades	Downgraded firms experience significant announcement effect in both pre-announcement and announcement windows. The announcement effect substentially stronger for speculative-grade than for investment-grade companies. Negliglible effect of rating upgrades.
Barron et al. (1997)	Equity	S&P	Negative market reaction to rating downgrades and positive market reaction to positive S&P watchlistings.
Goh and Ederington (1999)	Equity	Moody's: 483 downgrades, 312 upgrades	Stock markets react more negatively to downgrades to and within speculative category than to downgrades within investment-grade category. Reaction to single- and multiple- notch downgrades is similar. Stronger market reaction that experience high (absolute) pre-announcement returns.
Kliger and Sarig (2000)	Equity/Bond	Ratings announcments of Moody's on March 30, 1982, when the agency replaced/updated its rating scale	Significant price reaction in both equity and bond prices following the Moody's rating scale refinement. Support found for asset substitution theory: better than expected ratings imply gains for the debtholders and losses for the equity holders (and vice versa). Pricing impact stronger for highly leveraged firms.
Steiner and Heinke (2001)	Bond	S&P and Moody's: 356 downgrades, 190 upgrades, 125 negative reviews, 57 positive reviews	Significant abnormal returns following downgrades and negative watchlistings. No significant effect following the positive rating changes. Negative announcements anticipated by the markets already 90 days in advance. Markets overreact to the negative announcments: significant reversal found during the three weeks following the announcements. Strongest price reactions observed for corporate bonds and the lowest for the bank bonds.

Table 2.1 continued on next page

Table 2.1 continued from previous page

Authors	**Market**	**Rating Event Data**	**Findings**
Dichev and Piotorski (2001)	Equity	Moody's: 1195 downgrades, 361 upgrades	No reaction following upgrades. Substential negative abnormal returs following downgrades. Underperformance of downgrades spans up to three years after the announcement. Underperformance stronger for small, bellow-investment-grade firms.
Hull et al. (2004)	CDS	Moody's	Significantly positive adjusted spreads already before the actual downgrade event. Also reviews for downgrades appear to be anticipated; the authors report 38bp increase in spreads 90 days before the event. The announcement effect found to be significant only for negative reviews: for these, the average response was about 10bp.
Norden and Weber (2004)	Equity/CDS	S&P, Fitch, and Moody's:	Equity: Negative reaction to downgrades and negative reviews to S&P and Moody's, no reaction to Fitch announcments. Anticipation effect evident for both negative reviews, and downgrades. CDS: Positive adjusted spread response to negative reviews and downgrades for S&P and Moody's, no reaction to Fitch announcments.
Philippe et al. (2005)	Equity	Fitch, S&P, and Moody's around SEC's regulation Fair Disclosure on October 23, 2000: 1767 downgrades, 437 upgrades.	Informational impact of bond rating downgrades/upgrades is significantly greater after the implementation of SEC's Regulation Fair Disclosure on October 23, 2000, which gave rating agencies advantage over equity analysts with respect to accessing to the companies' private information.
Jorion and Zhang (2007a)	Equity	Fitch, S&P, and Moody's: 1195 downgrades, 361 upgrades	Negative reaction to downgrades and economically small positive reaction to upgrades. After conditioning on the rating before the announcmnent the asymmetry in reaction to downgrades/upgrades substentially decreases.

Table 2.1 continued on next page

Table 2.1 continued from previous page

Authors	Market	Rating Event Data	Findings
Konijn and Rijken (2010)	Equity	S&P and Moody's	Negative rating announcments are partially anticipated. No positive post-announcement effect if the announcment out of line with pre-announcement point-in-time credit model tendencies. Positive post-announcement effect effect when the announcement confirms the general credit model tendency. Significant market response to negative watchlist additions.
Panel B: Industry Reactions to Rating Signals			
Akhigbe et al. (1997)	Equity	Moody's: 354 downgrades, 184 upgrades.	Negative equity response (-1.03%) of the firms experiencing downgrade. Negative equity response of industry peers to downgrades (-0.19%). No significant reaction for the rating upgrades. Peer response significant only when the downgraded entity's equity response is negative.
Ismailescu and Kazemi (2010)	CDS	S&P: 94 positive rating events, 67 negative events	CDS: Downgrades anticipated by the market. Strong reaction to positive announcments. Weak response to negative events. Only positive events display spillover effects.
Jorion and Zhang (2010)	Equity	Fitch, S&P, and Moody's: 679 downgrades, 473 upgrades, covering 132 4-digit industries.	Equity: Negative reaction to downgrades for event firms as well as for industry competitors. No significant reaction for upgrades, except when conditioning for the rating of the event firm before the upgrade. Negative reaction to negative watch list for event firms. Spillover from negative watch list only in the cases in which the event firm is an investment-grade entity.

2.4 Hypotheses

2.4.1 Intra-Industry Informational Transfer (IIIT) Hypotheses

In this chapter, we define the intra-industry information transfer (IIIT) as the phenomenon whereby the firm-specific event of one firm in an industry can be used to make inference about the asset pricing distribution of the firm's industry-related peers. Our main aim is to verify whether firm-specific credit rating signals elicit

IIIT effect in pricing of the industry-wide component of credit risk. In particular, we study the industry-wide behavior of CDS spreads, since these bear the closest correspondence to the market assessment of firms' credit risk. In what follows, we formulate the hypotheses that are tested in the empirical section of the chapter.

Let u_E^I denote the measure of the *abnormal* spread behavior of the event-firm E from industry I, and let ϕ_E be the rating signal (e.g. rating downgrade) corresponding to the company E. If a rating signal contains new pricing-relevant information, this should first be reflected in the credit spread of the event-company itself. Formally:

$$\begin{aligned} H_0: &\quad E[u_E^I \mid \phi_E] = 0 \\ H_1: &\quad E[u_E^I \mid \phi_E] \neq 0. \end{aligned} \tag{2.1}$$

In general we expect negative (positive) rating signals to precipitate an increase (decrease) in the abnormal spread measure. One may also observe the cases in which the direction of the event-firm abnormal spread reaction is of the opposite than expected sign. For example, a downgraded entity may react to the signal by a negative change in its abnormal spread. This may happen if the downgrade is not as severe as expected by investors, leading to the investors' relief.

If the rating signal also contains information that is relevant for evaluating the creditworthiness of the event-firm's industry peers, we expect to observe abnormal behavior in the credit spreads of firms that are not directly related to the announcement, but come from the same industry as the event-company. Defining u_j^I as the measure of the abnormal credit spread behavior of company j from industry I, and retaining the event-firm nomenclature from above, we can state this hypothesis as:

$$\begin{aligned} H_0: &\quad E[u_j^I \mid \phi_E] = 0, \quad j \neq E \\ H_1: &\quad E[u_j^I \mid \phi_E] \neq 0, \quad j \neq E. \end{aligned} \tag{2.2}$$

One of the problems with the formulation of IIIT hypothesis in (2.2) is that it fails to take into account the direction and the magnitude of informational impact of the rating signal on the abnormal credit spread behavior of the event-firm. This is important if the event-firm reaction reflects the extent to which a rating signal was anticipated by the market[5]. Failing to condition on the event-firm response might lead to the rejection of IIIT, when, in fact, the informational transfer does take

[5] If the rating event is unanticipated, we expect the negative (positive) rating events to result in abnormal spread widening (narrowing).

place. To understand this point, note that the unconditional abnormal industry-peer response to the rating signal ϕ_E can be written as:

$$E[u_j^I \mid \phi_E] = Pr\{u_E^I \geq 0\}\; E[u_j^I \mid \phi_E,\ u_E^I \geq 0] + Pr\{u_E^I < 0\}\; E[u_j^I \mid \phi_E,\ u_E^I < 0]. \tag{2.3}$$

If $Pr\{u_E^I \geq 0\} < 1$ and the industry-response tends to be equi-directional with respect to the event-firm's response, i.e. $E[u_j^I \mid \phi_E,\ u_E^I \geq 0] \geq 0$ and $E[u_j^I \mid \phi_E,\ u_E^I < 0] < 0$, then the right-hand-side terms of (2.3) may cancel out, leading to the faulty rejection of IIIT. From the economic standpoint, the equi-directional industry response is to be expected when the signal reveals new information about the industry future prospects. In this case, good (bad) information for event-firm is also good (bad) information for its industry peers. In line with Giesecke (2004), we refer to such industry response as the instance of 'informational contagion'.

Informational contagion is consistent with several recently proposed theoretical models in the credit risk literature. Giesecke (2004) provides a structural multiple-firm model, in which investors know the processes followed by the assets of the companies, but are uncertain about each company's default barrier. Default barrier processes of the companies are assumed to be correlated, so that the credit event of one company allows investors to re-update their beliefs about the distribution of default barriers of the rest of the companies. By analogy, if rating announcements give investors new knowledge about the rated company's distance-to-default, and the distances-to-default are correlated across companies within the same industry, one may observe the intra-industry spread contagion after the rating event of a given company. Information contagion hypothesis is also consistent with the recent work of Collin-Dufresne et al. (2010a), where the authors outline the model in which the investors with the imperfect knowledge about the state of economy use any available information to update their beliefs about the current state. Contagious price response in this model occurs whenever the information released to the market contains information relevant for determining the current state of economy. As described in 2.2, bond rating announcements may contain such information.

The hypothesis about the presence of the contagious IIIT may be formulated as follows:

$$\begin{aligned} H_0:&\quad E[u_j^I \mid \phi_E,\ u_E^I \lesseqqgtr 0] \gtreqqless 0, \quad j \neq E \\ H_1:&\quad E[u_j^I \mid \phi_E,\ u_E^I \lessgtr 0] \lessgtr 0, \quad j \neq E. \end{aligned} \tag{2.4}$$

Alternatively, industry-peers may exhibit responses of the opposite direction relative to the response of the event-firm. For example, in an oligopolistic industry characterized by high entry barriers, a signal of financial deterioration in one of the market players may be a good news for its competitors, since they may expect to benefit from increased monopolistic rents, if the event-firm were to go bust. This, in turn, would increase their expected creditworthiness and narrow their credit spread, while the spreads of the event firm might actually increase. The literature (e.g. Lang and Stulz (1992), Jorion and Zhang (2007a), etc.) refers to such information transfer as the 'competitive IIIT'. The competitive IIIT hypothesis can be formulated as:

$$\begin{aligned} H_0: &\quad E[u_j^I \mid \phi_E,\ u_E^I \lesseqgtr 0] \lesseqgtr 0, \quad j \neq E \\ H_1: &\quad E[u_j^I \mid \phi_E,\ u_E^I \lesseqgtr 0] \gtreqless 0, \quad j \neq E. \end{aligned} \tag{2.5}$$

Notice that contagious and competitive IIIT hypotheses are mutually exclusive so accepting one necessarily refutes the other (but not vice versa, due to the possibility of no abnormal response).

2.4.2 Conditional IIIT Hypotheses

Theoretically and empirically, the nature and the magnitude of IIIT effect may depend on several factors. It may depend on the nature of the rating signal ϕ_E, on characteristics of the event-firm and on characteristics of the industry. We consider each of the three aspects in turn.

First, rating agencies provide markets with four main types of rating signals[6]: rating downgrades, rating upgrades, and reviews for downgrades/upgrades[7]. Authors like Hand et al. (1992), Hite and Warga (1997), Hull et al. (2004), Norden and Weber (2004) demonstrate that negative rating signals induce stronger market responses than positive rating announcements in the valuation of event-firms' assets. If the magnitude of an IIIT effect is positively related to the magnitude of the response of the event-firm (i.e. $|E[u_j^I \mid \phi_E,\ u_E^I \lesseqgtr 0]| > |E[u_j^I \mid \phi_E,\ u_E^{I*} \lesseqgtr 0]|$, where $|u_E^I| > |u_E^{I*}|$), then upon observing the asymmetry of responses of event firms, one may also expect to observe asymmetry in the responses of industry peers. Let $\phi_E^{(P)}$ denote the positive rating signals (i.e. rating upgrades, and positive reviews) and let $\phi_E^{(N)}$ stand for

[6]In fact, rating agencies provide more types of signals, e.g. rating outlooks. In line with the existing capital markets literature we only focus at downgrades, upgrades, and reviews for downgrades/upgrades.

[7]Also know as negative/positive watch-listings in the parlance of S&P and Fitch.

the negative rating signals (i.e. rating downgrades, and negative reviews). The asymmetric-response hypothesis may be formulated as follows:

$$\begin{aligned} H_0: &\ \mid E[u_j^I \mid \phi_E^{(N)},\ u_E^I(\phi_E^{(N)}) \lesseqgtr 0] \mid = \mid E[u_j^I \mid \phi_E^{(P)},\ u_E^I(\phi_E^{(P)}) \lesseqgtr 0] \mid, \quad j \neq E \\ H_1: &\ \mid E[u_j^I \mid \phi_E^{(N)},\ u_E^I(\phi_E^{(N)}) \lesseqgtr 0] \mid > \mid E[u_j^I \mid \phi_E^{(P)},\ u_E^I(\phi_E^{(P)}) \lesseqgtr 0] \mid, \quad j \neq E. \end{aligned} \tag{2.6}$$

Given the type of a rating signal, the magnitude of the IIIT may also depend on other event characteristics, such as the strength of the signal (e.g. number of notches downgraded/upgraded, crossing of investment/speculative grade boundary due to rating change, etc.), agency providing the signal, timing of the signal (e.g. boom/bust period), etc. For example, Jorion and Zhang (2010) find that other things being equal, the IIIT in the equity markets is stronger in the cases in which the downgraded entity falls below the investment-grade boundary. Norden and Weber (2004) find that market reactions are significant for S&P and Moody's announcements but not for Fitch. Let ϕ_E and ϕ'_E be two signals that are of the same type (e.g. both downgrades) but which differ in one of the event-type characteristics. The hypothesis of heterogeneous IIIT effect due to the heterogeneous event characteristic is given as:

$$\begin{aligned} H_0: &\ E[u_j^I \mid \phi_E,\ u_E^I(\phi_E) \lesseqgtr 0] \ = \ E[u_j^I \mid \phi_E^{'},\ u_E^I(\phi_E^{'}) \lesseqgtr 0] \mid, \ \ j \neq E,\ \phi_E \neq \ \phi'_E, \\ H_1: &\ E[u_j^I \mid \phi_E,\ u_E^I(\phi_E) \lesseqgtr 0] \ \neq \ E[u_j^I \mid \phi_E^{'},\ u_E^I(\phi_E^{'}) \lesseqgtr 0] \mid, \ \ j \neq E,\ \phi_E \neq \ \phi'_E. \end{aligned} \tag{2.7}$$

Alternatively, the magnitude and the direction of the IIIT effect may depend on the event-firm and industry-specific characteristics. For example, Akhigbe, Madura, and Whyte (1997) find that highly leveraged industries exhibit stronger contagion effects than the industries with relatively small leverage, the intuition being that highly leveraged industries are more vulnerable to negative economic shocks. Letting x_E and x_I represent event-firm and industry characteristics, respectively, the hypothesis of heterogeneous IIIT effect due to heterogeneous firm-specific and industry-specific characteristics, can be stated as:

$$\begin{aligned} H_0: &\ E[u_j^I \mid \phi_E,\ u_E^I(\phi_E) \lesseqgtr 0,\ x_k] \ = \ E[u_j^I \mid \phi_E,\ u_E^I(\phi_E) \lesseqgtr 0,\ x'_k] \mid, \ \ j \neq E, \\ &\qquad\qquad x_k \neq \ x'_k,\ k \in \{E, I\} \\ H_1: &\ E[u_j^I \mid \phi_E,\ u_E^I(\phi_E) \lesseqgtr 0,\ x_k] \ \neq \ E[u_j^I \mid \phi_E,\ u_E^I(\phi_E) \lesseqgtr 0,\ x'_k] \mid, \ \ j \neq E, \\ &\qquad\qquad x_k \neq \ x'_k,\ k \in \{E, I\}. \end{aligned} \tag{2.8}$$

Table 2.2 presents the event-, firm-, and industry-specific characteristics used in this chapter to test (2.7) and (2.8).

2.5 Data

2.5.1 Rating Announcement Dates

We collect the rating announcement dates during the period between January 2003 and April 2011 from Bloomberg Terminal. Rating announcements come from S&P, Moody's, and Fitch and include four types of rating events: downgrades, upgrades, reviews for downgrades, and reviews for upgrades. The raw dataset of announcements contains 1341 downgrades, 808 upgrades, 753 negative reviews, and 243 positive reviews. The event-dataset used in the subsequent empirical analysis is smaller due to the pricing and accounting data availability as well as because of the data-cleaning procedures described later in this section.

Panels A and B of Table 2.2 give the summary of the final event-dataset. Majority of rating events come from S&P and Fitch. The sector-wide composition of rating events presented in Panel A reveals that rating activity documented in this dataset is concentrated in Consumer Discretionary and Financials categories. One can also notice that in relative terms S&P and Moody's use the rating review signals more often than Fitch. The analysis of time distribution of rating events (presented in appendix) testifies to the increased downgrading activity during the period following Lehman Brother's default, suggesting that rating agencies had failed to capture the deteriorating fundamentals before the crisis. Panel B shows the distribution of the magnitude of rating changes for rating downgrades and upgrades. The magnitude of rating change is defined as the absolute value of the difference between the old rating and the new rating, both expressed in the number notches above zero, where zero stands for default. The magnitude of most rating changes is one or two notches, and about one third of downgrades and upgrades result in transition over the investment/speculative-grade boundary[8].

2.5.2 Credit Default Swap Dataset

This study features the longest span of the daily CDS data considered in the market efficiency literature so far. We build the CDS dataset from two different data

[8]Between BBB- (Baa3) and BB+ (Ba1) according to S&P or Fitch (Moody's) rating scale.

Table 2.2 – Description of the Dataset. Panels A, B, and C summarize the final sample of events. We consider four types of rating events (downgrades, upgrades, reviews for downgrade, and reviews for upgrade) announced by S&P, Moody's or Fitch. Panels D, E, and F describe the final CDS pricing data. Between January 1, 2003, and December 14, 2007, the CDS data come from CMA. After that and until March 28, 2011, the data is taken from Thompson Reuters CDS pricing service.

Panel A: Industry Distribution of Events

GICS 2-digit code	Industry Name	# of Downgrades			# of Upgrades			# of Negative Reviews			# of Positive Reviews		
		S&P	Moodys's	Fitch	S&P	Moodys's	Fitch	S&P	Moodys's	Fitch	S&P	Moodys's	Fitch
10	Energy	23	1	13	31	11	21	20	2	1	16	9	1
15	Materials	41	11	9	33	4	9	30	3	1	16	1	1
20	Industrials	55	7	24	37	5	19	53	5	5	14	4	1
25	Consumer Discretionary	154	18	79	63	16	53	92	13	9	18	12	1
30	Consumer Staples	33	7	17	8	3	12	33	8	0	7	1	1
35	Health Care	30	8	25	42	3	21	20	4	9	12	1	1
40	Financials	98	26	65	44	8	42	68	15	20	9	7	4
45	Information Technology	25	3	14	15	1	21	20	3	1	7	1	0
50	Telecommunication Services	26	7	23	6	3	12	30	4	6	5	4	2
55	Utilities	46	14	34	21	5	21	30	12	5	10	5	9
Total		531	102	303	300	59	231	396	69	57	114	45	21

Panel B: Distribution of downgrades/upgrades by the absolute magnitude of rating changes

Absolute magnitude of rating change	# of Downgrades			# of Upgrades		
	S&P	Moody's	Fitch	S&P	Moody's	Fitch
1	395	79	230	256	46	189
2	95	20	42	35	11	33
3	19	3	19	5	0	7
4	8	0	7	0	0	0
5	7	0	2	1	1	1
6	3	0	2	1	0	0
7	2	0	1	1	1	0
8	2	0	0	1	0	0
Crossing of Investment/Spculative Grade Boundary	65	7	46	38	5	24
Crossing of Major Rating Classes	207	37	127	107	19	80

Table 2.2 continued from the previous page

Panel C: Number of CDS spread observations and number of underlying reference entities by year and by S&P Issuer credit rating

Year	AAA/AA		A		BBB		BB		B or below		Complete	
	# of obs.	# of entities*	# of obs.	# of entities	# of obs.	# of entities	# of obs.	# of entities	# of obs.	# of entities	# of obs.	# of entities
2003	6326	26	28794	113	41498	160	11270	42	3723	10	91611	351
2004	6021	24	28046	110	42740	166	11139	39	4016	12	91962	351
2005	5680	22	26291	107	43422	171	11676	37	4191	14	91260	351
2006	5895	24	25128	100	42983	169	11814	42	5440	16	91260	351
2007	6352	35	24524	127	41775	224	13963	72	6569	24	93183	482
2008	8439	36	31551	122	56896	220	19871	73	9527	31	126284	482
2009	6129	25	29843	122	56399	221	19113	69	14318	45	125802	482
2010	6003	23	29406	117	56746	215	18159	70	15488	57	125802	482
2011	1230	23	6245	114	11990	218	3625	68	3420	59	26510	482
Complete	52075	43	229828	181	394449	307	120630	149	66692	79	863674	482

Panel D: Number of CDS observations for a firm

	Mean	Median	Std. Dev.	Min	Max
All	1444.741	1877	577.1739	131	2142
% of observations with no change in spread	35.16	28.42	20.61	5.64	99.16

Panel E: Number of firms in an 8-digit GICS industry portfolio (excluding event firms)

	Mean	Median	Std. Dev.	Min	Max
All	4.64991	4	3.200733	1	20

Panel F: CDS Spread Levels (Skewness= 7.74 , Kurtosis= 85.45)

Year	Frequency	Mean	Std. Dev.	Min	1st perc.	Median	99th perc.	Max
2003	93,960	130.75	127.83	10.61	11.98	90.00	518.41	785.27
2004	94,320	76.80	91.94	1.00	8.60	44.80	490.00	955.00
2005	93,600	83.74	143.98	1.10	8.80	42.30	582.00	2751.70
2006	93,600	75.98	108.24	1.00	6.50	37.50	542.50	1796.40
2007	95,904	94.00	139.05	1.00	7.30	42.80	649.20	2166.62
2008	136,764	286.28	499.68	5.00	27.00	117.00	2612.17	9234.42
2009	136,242	413.47	809.98	13.14	27.24	156.43	4455.16	11604.00
2010	136,242	237.60	490.48	15.42	26.29	118.68	1594.39	15184.48
2011	28,710	204.75	518.91	14.89	24.01	105.18	1494.31	10516.18

Panel G: CDS Spread Changes (Skewness= 0.092, Kurtosis=121.29)

Year	Frequency	Mean	Std. Dev.	Min	1st perc.	Median	99th perc.	Max
2003	93,960	-0.51	11.95	-375.27	-20.50	0.00	16.07	372.77
2004	94,320	-0.06	7.33	-420.00	-14.20	0.00	13.91	426.50
2005	93,600	0.10	14.50	-955.00	-15.00	0.00	17.40	1877.30
2006	93,600	-0.11	7.26	-1006.40	-12.50	0.00	11.30	996.40
2007	95,904	0.34	8.26	-358.50	-19.50	0.00	24.70	356.70
2008	136,764	1.58	45.25	-4797.31	-45.63	0.00	75.00	4567.05
2009	136,242	-1.23	71.82	-4696.77	-85.00	0.00	61.29	6611.46
2010	136,242	-0.04	33.05	-3544.13	-28.50	0.00	28.78	5481.07
2011	28,710	-0.26	14.29	-1107.05	-19.08	0.00	15.00	474.99

* We count a number of reference entities that were in a rating category once during a year. If a company is downgraded/upgraded during a year, it is thus counted twice. As a result the number of entities in each rating category does not necessarily add up to the total number of entities reported in the last column of Panel C.

sources. Between January 1, 2003, and December 14, 2007, the data come from CMA-CDS database, whereas after that and until March 28, 2011, the data is taken from Thompson Reuters CDS pricing service. Both providers produce their spread data by collecting daily quotes from major financial institutions that trade with CDS contracts. After removing outliers and stale observations, the daily quotes are averaged and provided to the end user.

The raw dataset consists of all available single-name CDS spreads of U.S. industrial and financial corporations during the aforementioned periods. In line with the existing research, we only focus at the contracts with 5 year maturities and with the Modified Restructuring clause (e.g. see Norden and Weber (2004)). These contracts represent the most liquid and the most traded class of CDS securities.

Panels C, D, F, and G of Table 2.2 present the summary of the final CDS dataset (the data-cleaning procedure is described in the next section). Panel C reveals that majority of CDS observations come from BBB rated issuers and from the period between 2007 and 2011. The latter observations is attributable to the higher coverage of the Thompson Reuters data in comparison to CMA[9]. In total the final dataset covers 482 reference entities and consists of 863,674 daily observations. Panel D reveals that the average length of the time series of CDS spreads for each reference entity is 1444 days, and that on average 35% of daily spread observations exhibit no change[10].

Panels F and G report summary statistics for the CDS spread levels and changes, respectively. The average spread levels were generally below 100 basis points before the Lehman's default in 2008, they reached unprecedented heights during the years 2008 and 2009 (286 b.p. and 413 b.p., respectively) and then slowly declined during the two years to come. The maximum observed spread exceeds 15000 b.p., or 150% of the CDS notional. Such high spreads can be explained by noting that they occur in situations in which the reference entity is almost certain to file for bankruptcy within a few weeks or months. For example, if the entity is sure to default within a month and is expected to have no recovery value, its annualized CDS spread would equal approximately $12 \times 100\% = 1200\% = 120,000\ b.p.$[11].

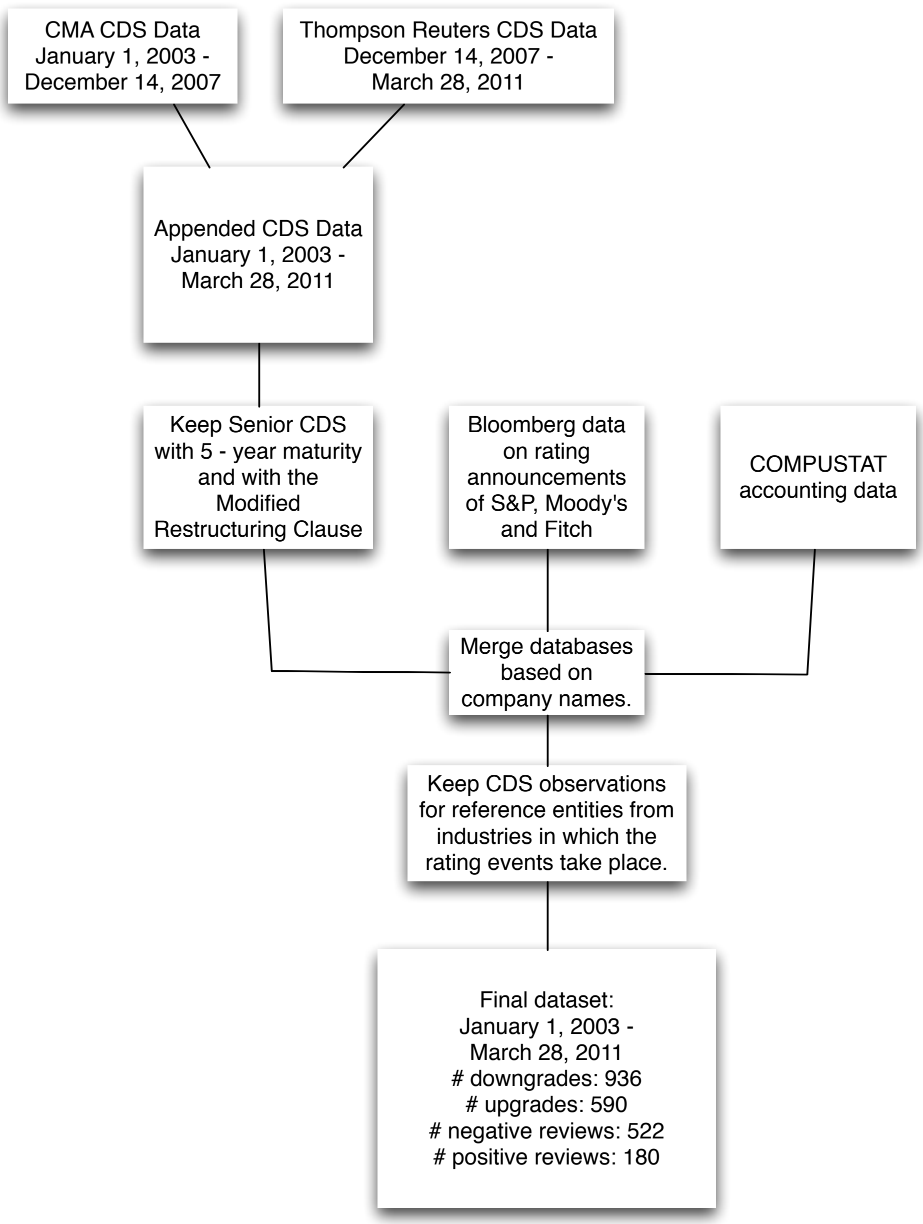
The story is similar when looking at the spread changes. During 2007 and 2008 the average spread changes were positive, reflecting a general deterioration in credit quality during that time. Generally, the distribution of spread changes

[9]Note that CMA data covers the period between 2003 and 2007.

[10]Such fraction of no-change observations is in line with Jorion and Zhang (2007a), whose study covers the period between 1998 and 2002.

[11]See Hull et al. (2004), p. 2794.

Figure 2.3 – Dataset construction process.



is concentrated at zero and exhibits extremely fat tails. This warrants a caution when applying standard parametric-based inferences that are routinely used in the equity-based event studies.

2.5.3 Data Cleaning Procedures

Preparation of the final dataset presented in the previous section necessitated several cleaning and selection steps. Figure 2.3 provides a rough outline of the selection process. After appending CMA and Thompson Reuters CDS data we merged the resulting dataset with Compustat accounting data and with the Bloomberg dataset of rating events. The lack of a common identifier across the three databases necessitated the merger on the basis of company names[12]. In order to be included in the final dataset, an *entity* had to pass two additional filters:

1. It had to experience a rating event *or* had to come from the 8-digit Global Industry Classification Standard (GICS) industry in which the event had taken place.
2. CDS data had to be available for at least 10 days before and after the rating event.

One of the main concerns related to the estimation of the informational impact of a rating signal is that the event window under consideration may be contaminated by other news that influence the magnitude of a spread[13]. In order to mitigate such considerations, we posed several additional requirements for the *events* that were included in the subsequent statistical test. Specifically:

1. We excluded all simultaneous events for a given industry.
2. If several rating announcements occurred in an industry within a 15-day window, we only kept the first event in the window and discarded the others[14].

[12]We proceeded in two steps. First we applied a string-matching algorithm, which found approximately 60% of the final number of matches (all algorithm-based matches were manually verified for consistency). The rest of the matches were found manually.

[13] Traditionally, the market efficiency literature on rating signals attempts to control for two main sources of information contamination. First is the within-agency contamination, which may occur when a given rating agency issues several announcements pertaining to a given issuer within a short period of time (i.e. within the same event window). Second is the across-agency contamination, which may take place when a given issuer is rated by several rating agencies. These may publish their ratings, pertaining to the same underlying change in the issuer's creditworthiness, simultaneously or within a short time-span. Both, within and across-agency contamination may hamper causal inference about the informational content of rating announcements, because they conceal the link between a given rating event and the observed market reaction.

[14] In order to verify the robustness of our results, we applied alternative data cleaning schemes, in which the exclusion criteria were more severe (in particular, the cleaning windows were set to be larger). Under these schemes the result remained qualitatively and statistically similar to the results reported here.

After applying all of the filters mentioned above our raw sample of events reduced by about 65%, a proportion that is roughly consistent with the existing studies which implement similar filtering schemes (Galil and Soffer, 2011).

2.6 Methodology

The main focus of this chapter is to empirically test for the presence of informational transfers induced by rating signals in the markets for corporate credit risk. To this end, we use a variant of event study methodology, which is adapted to the analysis of CDS spreads.

2.6.1 Measuring the Abnormal Credit Spread Behavior

The hypotheses developed in 2.3 are formulated in terms of *abnormal spread behavior* around the announcements of rating signals. Using raw CDS spread changes as the measure of the abnormal spread behavior is inappropriate because raw spreads also reflect the general market factors, which influence the spreads of all companies in the market. Failure to control for these factors might lead to the faulty appraisal or refutal of the hypotheses tested in this chapter.

In order to exclude the general market influences, we follow the procedure that is commonly used to measure abnormal spread performance in the CDS market efficiency literature (see Hull et al. (2004), Norden and Weber (2004), Jorion and Zhang (2007a), Jorion and Zhang (2009), Ismailescu and Kazemi (2010)).

First, we formulate five CDS indices based on credit ratings of the underlying CDS reference entities. Each index is constructed as the spread on the equally weighted portfolio of CDS on reference entities coming from five broad rating categories, AAA/AA (Aaa, Aa), A, BBB (Baa), BB (Ba), and B or below. An issuer is included in the index according to its S&P issuer rating. If the S&P rating is unavailable, we use the issuer's rating made by Moody's or Fitch. We additionally require that the company included in the index at date t experiences no rating event 15 days prior or after the date t.

Second, in line with Norden and Weber (2004) we define *Abnormal CDS Spread Change (ASC)* as the CDS spread change of firm i at time t adjusted for the spread change of the corresponding rating index:

$$ASC_{i,t} = \begin{cases} (CDS_{i,t} - CDS_{i,t-1}) - (I_{o,t} - I_{o,t-1}), & \text{if } t < 0 \\ (CDS_{i,t} - CDS_{i,t-1}) - (I_{n,t} - I_{n,t-1}), & \text{if } t \geq 0, \end{cases} \tag{2.9}$$

where $I_{o,t}$ is the level of rating-based CDS index corresponding to firm i's rating category *before* the event, and $I_{n,t}$ is the level of the index corresponding to firm i's rating category *after* the event. Time index t equals zero on the day of rating announcement. We compute the *cumulative abnormal CDS spread change* for an entity i during the time interval beginning at t_1 and ending at t_2 as:

$$CASC_i\,[t_1, t_2] = \sum_{t=t_1}^{t_2} ASC_{i,t}. \tag{2.10}$$

2.6.2 Industry Portfolio Construction

The first step in a study of industry responses incited by rating events is to define the criteria for a construction of industry portfolios. We define an industry portfolio as the equally weighted CDS portfolio of reference entities which come from the same 8-digit GICS[15] industry as the event-firm. We emphasize that event-firms are excluded from industry portfolios, since including them would likely skew results in favor of contagious IIIT.

We measure the abnormal industry spread behavior following the methodology introduced above. In particular, if event firm i belongs to the 8-digit GICS industry J, the corresponding Industry Abnormal CDS Spread Change (IASC) is defined as:

$$IASC_{J,t} = \frac{1}{N_{J,t}} \sum_{z \in J,\, z \neq i} ASC_{z,t}, \tag{2.11}$$

where $N_{J,t}$ is the number of firms in industry J at time t, excluding the event firm. Finally, the cumulated industry abnormal spread change (Cumulative Industry Abnormal CDS Spread Change (CIASC)[16]) is obtained by summing up the daily IASCs:

$$CIASC_J\,[t_1, t_2] = \sum_{t=t_1}^{t_2} IASC_{J,t}. \tag{2.12}$$

[15]GICS (Global Industry Classification Standard) is an industry taxonomy developed S&P. Bhojraj et al. (2003) report that GICS industry classification is significantly better than SIC or NAICS classifications for applications in the capital market studies, since it provides a superior account of the stock return co-movements and displays higher degree of consistency over time. The GICS classification is routinely used in the private sector and is becoming increasingly popular in academia (e.g. Xu et al. (2006)).

[16]I thank Ton Vorst for suggesting such nomenclature.

2.6.3 Statistical Tests for Analyzing the Abnormal CDS performance

A closer examination of Cumulative Abnormal CDS Spread Change (CASC)s and CIASCs reveals that their distribution is highly non-normal. In particular, it displays extremely fat tails ($Kurtosis \approx 185$) and a high degree of skewness. As a result, the standard parametric tests used in equity-based event-studies may be misleading when applied in our setting. Because of this we decide to base our analysis primarily on non-parametric tests, in particular the Corrado rank test. Corrado (1989) provide a non-parametric rank test which remains well specified even when the underlying distribution is skewed and has fat tails. A broad body of simulation-based literature has established that the test exhibits higher power to detect abnormal security performance than any other commonly used parametric or non-parametric test, especially in the situations in which the underlying distribution is highly non-normal. Under the null hypothesis of no abnormal performance the Z-statistic of the test is approximately standard-normally distributed. The computational details on the test can be found in the Appendix.

As a robustness check we also provide results of the Generalized Sign Test. The test compares the proportion of positive (negative) CIASC observations during the event window with the proportion of positive (negative) observations during the normal market performance (rather than with 0.5 as is the case in the standard Sign Test). We compute proportions under normal performance during the [-250,-20] and [20,250] time intervals.

2.7 Empirical Results

2.7.1 Univariate Results

In this section we test the hypotheses formulated in (1), (2), (4), and (5). Our measures of abnormal spread performance in the announcement window are CASC for event-firms, and CIASC for their industry-peers, both measured over the [-1,1] event period. We also performed the tests using the alternative event-window lengths. Since the results remained broadly consistent with the ones for the [-1,1]-interval, we omit them for the sake of brevity.

Table 2.4 presents the main results in this section. It shows the event-firm and industry abnormal spread responses to four types of rating signals (downgrades, upgrades, negative/positive reviews) announced by the S&P, Moody's, and Fitch. The industry responses are presented for the total sample of events, and for two subsamples stratified by the sign of the event-firm response. The latter two subsamples are used to test for contagious/competitive IIIT whereas the former is tested for the unconditional IIIT.

Hypothesis (1): Information Content of Rating Signals for Event-Firms

For S&P announcements, mean and median event-firm market reactions are significant and of expected sign for all four types of events. Abnormal spreads changes are positive following negative rating signals, and negative following positive rating signals. In the case of S&P downgrades (negative reviews) event-firm abnormal spreads jump on average by 19 b.p. (18 b.p.) whereas for upgrades (positive reviews) we observe averages abnormal spread drops of about 4 b.p. (16 b.p.). Event-firm market reactions are less clear in the case of announcements by Moody's and Fitch. For Moody's only the responses to positive rating signals are statistically significant and of the expected sign, while for Fitch no clear pattern can be established. In the context of the past literature, the latter result is puzzling for Moody's but not for Fitch rating signals. Insignificance of Moody's negative announcements might stem from small sample size, while insignificance of results for Fitch supports the findings of Norden and Weber (2004) who find that Fitch announcements tend to add little new information. S&P rating signals appear to be the most important source of information for pricing credit risk of reference entities related to announcements. This observation concurs with the findings of Gande and Parsley (2005) and Norden and Weber (2004) who find *S&P* announcement to be the most informative, judged both in terms of economic and statistical significance of market reactions.

Hypothesis (2): Unconditional IIIT

Next, we turn to the industry peer reactions. First, we study the unconditional peer responses around the rating events. The principal observations are as follows:

1. Unconditional peer responses to the negative rating events tend to be statistically insignificant and exhibit no clear directional pattern over the agencies or over the two types of negative signals.

2. Unconditional peer responses to the positive rating events are statistically significant for S&P but not for the other two agencies. In absolute terms, the

average peer response amounts to 2b.p. drop in abnormal spread for both types of positive announcements (looking at S&P only).

The first of the two observations is somewhat surprising given that we find a strong event-firm reaction of spreads around the negative rating signals, in particular around negative reviews. However, as we see in the next section, conditioning industry responses on the direction of event firm response reveals statistically and economically significant IIIT also for the negative rating events. The second observation seems to suggest that positive rating signals by S&P contain large component of industry-wide information.

Hypotheses (4) and (5): Contagious vs. Competitive IIIT

We test for the contagious (competitive) IIIT by stratifying portfolio CIASCs according to the sign of event firm reaction to a rating event and then testing whether the response in each of the two subsamples is consistent with contagious, competitive, or no IIIT. The main observations are summarized in the following points:

1. In the case of S&P announcements, we observe a strong evidence of contagious IIIT for all four types of announcements. Contagious IIIT exhibits a high level of economic and statistical significance particularly in the cases in which the event-firm's reaction to a rating signal has its predicted sign (i.e. when event-firm spreads widen after negative rating events and narrow after positive rating events). These are likely to be the events in which the rating signal had not been anticipated, or had been more severe than anticipated by the market.

2. For Moody's and Fitch results are mixed. We find some evidence of contagious IIIT in the case of negative reviews but the pattern for other types of rating events is far from clear.

3. Notably, we find no support for competitive IIIT in any of the cases.

The main takeaway from the observations outlined above is that the contagious IIIT is most potent in situations in which the rating announcement is made by S&P and in which the event-company reacts by positive abnormal spread change to negative, and by negative abnormal spread change to positive rating signals. Importantly, the contagious effect is not limited to negative rating announcements, but also takes place following positive rating announcements. This contrasts the

Table 2.4 – Abnormal CDS-Spread Responses to Rating Announcements (in b.p.). This table reports the mean and median [-1,1]-window cumulative abnormal CDS-spread responses by event-firms and their industry-related peers, to four types of rating events: downgrades, upgrades, negative reviews, and positive reviews. Abnormal CDS spreads are computed according to formula (3) and aggregated over three days around the announcement day (C(I)ASC stands for the cumulative (industry) abnormal spread change). Industry portfolios are constructed as the equally-weighted portfolios of firms with the same 8-digit GICS code as the firm that experiences the event, and with the available CDS pricing data. Event firms are excluded from the corresponding industry portfolios. In order to identify the presence of intra-industry information transfer, industry response is stratified according to the direction of the event-firm abnormal spread response ($CASC_{event}$) to the given event. For each type of event, the percentage of non-negative C(I)ASC responses is reported. The zero hypothesis of no abnormal announcement-window performance is tested by the means of the generalized sign test and the Corrado Ranksum test (the details on both tests are given in the appendix). We report the p-value of the Generalized Sign test in the single-square brackets, and the Z-statistic of the Corrado test in the double-square brackets. Corrado Z-statistic is approximately standard normally distributed under the null of no abnormal market performance.

	Downgrades				Upgrades			
	Event Firm	Industry Portfolios			Event Firm	Industry Portfolios		
		All	$CASC_{event} \geq 0$	$CASC_{event} < 0$		All	$CASC_{event} \geq 0$	$CASC_{event} < 0$
Panel A: S&P								
# of Obs.	478	478	305	173	278	278	143	135
Mean CIASC	19.310	0.386	3.730	-5.511	-4.305	-1.606	-1.337	-1.891
Median CIASC	0.032	-0.013	0.527	-2.091	-0.013	-0.348	0.000	-0.499
% of $C(I)ASC \geq 0$	63.81	49.16	58.36	32.95	51.44	41.73	49.65	33.33
Gen. Sign Test p-value	[0.000]	[0.891]	[0.001]	[0.000]	[0.675]	[0.019]	[0.867]	[0.000]
Corrado Ranksum Z-stat.	[[3.583***]]	[[-0.122]]	[[2.634***]]	[[-2.853***]]	[[-2.934***]]	[[-2.691***]]	[[-0.632]]	[[-3.272***]]
Panel B: Moody's								
# of Obs.	87	87	58	29	48	48	28	20
Mean CIASC	4.388	-2.263	1.597	-9.983	-0.275	1.443	2.535	-0.086
Median CIASC	0.018	-0.343	-0.165	-1.108	0.000	0.156	-0.083	0.497
% of $C(I)ASC \geq 0$	66.67	42.53	46.55	34.48	58.33	50.00	46.43	55.00
Gen. Sign Test p-value	[0.002]	[0.198]	[0.694]	[0.136]	[0.312]	[0.885]	[1.000]	[0.824]
Corrado Ranksum Z-stat.	[[0.266]]	[[-1.224]]	[[-0.224]]	[[-1.712*]]	[[-2.063**]]	[[0.439]]	[[-0.024]]	[[0.693]]
Panel B: Fitch								
# of Obs.	274	274	172	102	220	220	111	109
Mean CIASC	1.816	-3.618	0.057	-9.816	-3.203	-0.388	0.225	-1.012
Median CIASC	0.011	0.118	0.720	-0.936	0.000	-0.528	-0.340	-0.737
% of $C(I)ASC \geq 0$	62.77	51.82	56.40	44.12	50.45	43.64	45.05	42.20
Gen. Sign Test p-value	[0.000]	[0.506]	[0.079]	[0.276]	[0.946]	[0.068]	[0.343]	[0.125]
Corrado Ranksum Z-stat.	[[0.166]]	[[-0.205]]	[[0.945]]	[[-1.206]]	[[-1.025]]	[[-0.839]]	[[0.771]]	[[-1.451*]]

	Negative Reviews				Positive Reivews			
	Event Firm	Industry Portfolios			Event Firm	Industry Portfolios		
		All	$CASC_{event} \geq 0$	$CASC_{event} < 0$		All	$CASC_{event} \geq 0$	$CASC_{event} < 0$
Panel A: S&P								
# of Obs.	347	347	260	87	106	106	49	57
Mean CIASC	17.980	2.307	4.212	-3.386	-16.370	-1.913	-0.0715	-3.497
Median CIASC	0.379	0.128	0.311	-0.393	-0.414	-0.252	-0.0958	-1.212
% of $C(I)ASC \geq 0$	74.93	51.59	54.23	43.68	46.23	41.51	48.98	35.09
Gen. Sign Test p-value	[0.000]	[0.591]	[0.093]	[0.284]	[0.497]	[0.098]	[1.000]	[0.033]
Corrado Ranksum Z-stat.	[[5.458***]]	[[1.242]]	[[2.033**]]	[[-0.905]]	[[-2.702***]]	[[-2.264**]]	[[0.372]]	[[-3.092***]]
Panel B: Moody's								
# of Obs.	58	58	38	20	38	38	18	20
Mean CIASC	10.450	4.289	8.770	-4.226	-5.041	0.013	0.701	-0.606
Median CIASC	0.012	0.157	0.770	-0.781	-0.737	0.015	0.0146	0.061
% of $C(I)ASC \geq 0$	65.52	53.45	63.16	35.00	47.37	52.63	55.56	50
Gen. Sign Test p-value	[0.024]	[0.694]	[0.143]	[0.263]	[0.871]	[0.627]	[0.481]	[1.000]
Corrado Ranksum Z-stat.	[[2.681***]]	[[1.282]]	[[2.779***]]	[[-1.531*]]	[[-2.835***]]	[[-0.002]]	[[0.844]]	[[-0.773]]
Panel B: Fitch								
# of Obs.	57	57	36	21	21	21	11	10
Mean CIASC	3.707	3.694	7.041	-2.045	-20.210	1.237	1.996	0.403
Median CIASC	0.801	-0.174	0.053	-1.631	0.000	0.801	2.194	-0.247
% of $C(I)ASC \geq 0$	63.16	47.37	52.78	38.10	52.38	66.67	81.82	50
Gen. Sign Test p-value	[0.062]	[0.791]	[0.868]	[0.383]	[1.000]	[0.189]	[0.065]	[1.000]
Corrado Ranksum Z-stat.	[[1.721**]]	[[0.142]]	[[1.384*]]	[[-1.313*]]	[[-2.127**]]	[[1.182]]	[[1.428]]	[[-0.902]]

[1] *, **, and *** denote significance at 10, 5 and 1% level, respectively.

equity-based results of Akhigbe et al. (1997) and Jorion and Zhang (2010), who find contagious effects only for downgrades.

2.7.2 Univariate Stratification Results: Testing the Conditional IIIT effects

The extent to which a given rating signal precipitates a contagious or competitive response in an industry portfolio may depend on event-firm characteristics, on industry characteristics, and on the characteristics of the event itself. The goal of this section is to find the cross-sectional determinants of IIIT effects. To this end we conduct a stratification analysis in which we analyze IIIT effects under alternative stratification schemes.

Since there exists little theoretical background on the determinants of IIIT effects, we proceed by selecting variables that, we believe, could be possible candidates in explaining heterogeneity of industry spread responses. Table 2.5 presents raw variables that we use in subsequent tests. The data comes from Compustat quarterly reports. In order to mitigate the influence of seasonal effects, all accounting variables are averaged over the past four quarters (on a rolling basis) before being transformed in financial ratios.

In order to test the conditional IIIT hypotheses (see 2.3) we proceed as follows. If a conditioning variable is continuous we split the sample of event-window CIASCs in terciles based on the value of the conditioning variable, and test whether the distributions of CIASCs in the three terciles are significantly different. To this end we apply the Kruskall-Wallis test, which is essentially a version of the well-known Mann-Whitney U-test, extended to three or more subsamples. When a conditioning variable is dichotomous, we test for the difference between the two sub-samples of CIASCs using the Mann-Whitney U-test.

In what follows, we present results for stratifications based on event-firm, industry, and event characteristics, in turn. In the previous section we found the strongest evidence in favor of IIIT effects in the case of S&P announcements. For this reason, as well as for the sake of brevity, the rest of the analysis in this chapter relies exclusively on these announcements and does not consider the announcements made by Moody's and Fitch.

Table 2.5 – Variables Used in Stratification and Multivariate Regression Analysis. This table presents the variables used in the stratification analysis (Tables 2.6, 2.7, and 2.8) and multivariate regression analysis (Table 2.12). The data used for the construction of the variables are taken from COMPUSTAT and include the quarterly accounting data for the North American entities during the period between January 2003 and March 2011.

Characteristic	**Variable**	**Definition**	**Included in the Final Regression**
Panel A: Event-Firm Characteristics (Raw Variables)			
Size	Total Assets	Natural logarithm of total book assets	Yes
Market Valuation	Market Equity-to-Book Equity Ratio	Market value of the firm's equity divided by its book equity*	No
Profitability	EBIT-over-Sales Ratio	Earnings before interest and taxes divided by total sales *	No
Leverage	Long-Term Debt Leverage	Long-term debt divided by total book assets*	Yes
	Short-Term Debt Leverage	Short-term debt divided by total book assets*	No
Liquidity	Current Ratio	Current assets divided by current liabilities *	No
Creditworthness	Event Firm Credit Quality	"Condensed" numeric rating scale ranging from 5 to 1, and corresponding to five broad rating categories, AAA/AA (Aaa, Aa), A, BBB (Baa), BB (Ba), and B or below, respectively.	Yes
Panel B: Industry Characteristics			
Size	Median Industry Total Assets	Median Total Assets in a 8-digit GICS industry on a given date	Yes
Market Concentration	Herfindahl Index	Sum of squared market shares for all COMPUSTAT firms coming from the same 8-digit GICS industry	Yes
Market Valuation	Market Equity-to-Book Equity Ratio		No
Profitability	EBIT-over-Sales Ratio		No
Leverage	Long-Term Debt Leverage	Equally-wighted industry average of the corresponding variables defined above	Yes
	Short-Term Debt Leverage		No
Liquidity	Current Ratio		No
Creditworthness	Industry Credit Quality		Yes
Industry Type	Financial/Non-Financial Corporation	Equals 1 if the event firm operates in the financial industry	Yes
Degree of Similarity with Event Firm	Correlation between Event-Firm and Industry Credit Spreads	Correlation between the equity returns*** of the event firm and the industry portfolio during 200 days before the event	Yes
Panel C: Event Characteristics			
Pre/Post-Crisis Period	Period Before / After Lehmann Brother's Failure	Equals 1 if the event happens after Lehmann's default	Yes
Severity of Rating Change	Magnitude of Rating Change	Equals 1 if the magnitude of rating change exceeds 1 tranche	No
	Crossing of Investment-Grade/Speculative-Grade Boundary	Equals 1 if the event firm crosses investment/speculative-grade boundary as a result of rating announcement	No
	Crossing of Major Rating Classes	Equals 1 if the event firm crosses a major rating class as a result of rating announcement	No

* Averaged over the preceeding four quarters.

** In the subsequent analysis, all event-firm based financial ratios are transformed in measures of relative event-firm performance within its industry. The relative performance measures are constructed by "standardizing" the raw levels of firm-specific variables, whereby we subtract the industry median level of the variable, and divide the difference by the within industry cross-sectional standard deviation of the variable. I.e. Relative value of variable X $= \frac{\text{Firm specific level of X} - \text{Industry median level of X}}{\text{Within industry cross sectional standard deviation of X}}$

*** Equity returns are obtained from CRSP.

Event-Firm Characteristics

For event-firms, our selection of variables relates to six dimensions of event-firm characteristics, which are size, market valuation (measured by market-to-book ratio), profitability, leverage, liquidity, and overall creditworthiness.

We acknowledge that the variation in event-firm-specific *levels* of the variables is prone to capturing industry, rather than firm-specific characteristics per se[17]. Since our interest here is primarily at IIIT effects contingent on how the event-firm fares relative to its industry competitors, we transform the firm-specific levels of variables into the measures of intra-industry relative performance within each class of characteristics. We do so by "standardizing" the raw levels of firm-specific variables. Specifically, we subtract the industry median level from the event-firm level of the stratification variable, and divide the difference by the within-industry cross-sectional standard deviation of the variable. Positive (negative) levels of the transformed variable thus correspond to over- (under-) performance of an event-firm relative to its industry peers within the considered dimension[18]. Exceptions to this treatment are event-firm size and creditworthiness. The relative event-firm size is measured as a ratio of the event-firm and industry-median total assets, whereas the relative event-firm creditworthiness is measured as the difference between the event-firm and industry-average level of creditworthiness (defined in Table 2.5).

Our predictions are as follows:

1. We expect to observe a positive relation between the relative event-firm size and the magnitude of contagious IIIT. The reason is that larger firms are more likely to be seen as industry leaders, and are therefore more likely to attract news coverage than their smaller industry peers. Additionally, financial problems of large firms are more likely to propagate to the rest of the industry through the direct counter-party channels, such as trade credits.

2. Following Jorion and Zhang (2010) we expect to observe contagious (competitive) IIIT when a negative rating signal relates to an investment-grade (speculative-grade) event-company. The argument is that a negative signal for a speculative-grade firm means a more likely withdrawal of the event-firm from the market, which, in line with competition theory, should increase competitors' profitability and, in turn, improve their creditworthiness. On the other hand,

[17] This is usually a consequence of the industry dynamics, in particular the nature of competition, operations, etc.

[18] Degree of under-performance is measured in the number of standard deviations.

a negative rating signal for an investment grade company is expected to be contagious due to the fact that these companies tend to be large and are thus likely to have a broader network of counterparty links. Alternatively, investment-grade companies tend to have a higher analyst coverage, which makes a spread of rating information (and a possible havoc induced by the information) to industry peers more potent.

3. Ex-ante, the influences of event-firm profitability and market valuation on IIIT are unclear. On one hand, a negative rating event of a highly profitable firm can signal an upcoming industry-wide deterioration of business conditions, and thus trigger contagious IIIIT. However, such event may also be cheered by competitors if it is believed that their business will benefit at the expense of the event-firm.

4. As before, the expected influence of leverage is unclear. From one side, highly leveraged event-firms might be the ones that are systemically more important, and are thus more likely to cause an industry downturn if their creditworthiness goes south. Oppositely, highly leveraged industries might be less formidable competitors if the debt service tames their ability to compete. Competition theories in this case suggest the prevalence of competitive IIIT.

Table 2.6 presents the results of the stratification analysis based on event-firm characteristics. The main observations are as follows:

1. Relative event-firm size is positively related to the strength of contagious IIIT in the case of negative rating events which elicit positive abnormal spread change reaction in event-firm spreads.

2. Event-firms with above average credit quality tend to precipitate stronger contagious IIIT effects following negative reviews accompanied by positive event-firm abnormal spread change. Oppositely, upgrades tend to be more contagious when they occur for below-average credit quality entities.

3. We find no statistically significant evidence of heterogeneous IIIT response over the groups stratified by relative profitability and market-valuation measures.

4. For relative leverage dimension, we observe a pattern similar to that in (1): negative rating signals seem to be more contagious when they occur for the highly leveraged companies (this only holds when the event-firm experiences

positive abnormal spread change). Only the influence of long-term debt is statistically significant.

5. When less liquid firms are hit by negative reviews, the IIIT effects tend to be more contagious than when the signal occurs for the relatively more liquid firms. For other rating signal, no statistically significant evidence of liquidity influence is observed.

Industry Characteristics

In this section we study the influence of industry characteristics on IIIT effects. Conditioning variables that we consider are similar to the ones studied in the previous section, with several important differences. First, industry-based financial ratios are constructed as equally-weighted averages of portfolio-constituting entity-based financial ratios. Second, instead of the size dimension, we consider industry concentration, which is measured by Herfindahl-Hirschman Index (HHI). HHI is constructed as a sum of squared market shares of *all* Compustat companies with 8-digit GICS code of the event company, in a quarter before the event takes place. Third, we introduce a measure that proxies for the cash-flow similarity between the event firm and its industry peers. To this end we use a correlation between the equity returns[19] of the event firm and the industry portfolio during 200 days before the event. Finally, we check whether IIIT effects differ across non-financial and financial companies.

The expected influence of each of the industry characteristics is considered in the following points.

1. In line with the industrial organization literature we expect competitive IIIT effects to be more prevalent in highly concentrated industries than in the less concentrated ones. Firms in highly concentrated industries are more likely to benefit (lose) from deteriorating (improving) industry peer's prospects than firms in competitive markets. This is because failure (success) of a rival has a stronger impact on the residual demand for goods and services of the remaining firms.

2. In the case of industry market valuation and profitability the direction of influence on IIIT is unclear. Currently, there is no theoretical literature that would guide the prediction in this case.

[19] Obtained from CRSP.

Table 2.6 – Industry Responses to the S&P Rating Announcements - Responses Stratified by Event-Firm Characteristics (in b.p.). This table presents the [-1,1] cumulative industry abnormal spread changes (CIASC) stratified by the characteristics of the event-firm (i.e. the firm that experiences the rating announcement). The CIASC calculation and the construction of industry portfolios is the same as before. We consider four broad classes of the event-firm characteristics: size and creditworthiness (Panel A), profitability and market valuation (Panel B), leverage (Panel C), and liquidity (Panel D). Within each of these classes we condition the CIASCs on several performance measures that correspond to a particular characteristic (the definitions of the variables used are provided in Table 2.5). We transform the raw levels of event-firm conditioning variables into the standardized deviations from industry means (and in some cases medians) in order to obtain the measures of event-firms' performance relative to their industry peers (see the footnote in Table 2.5 for the additional details on the procedure). We sort the sample of all CIASCs in terciles based on the values of the transformed conditioning variable (the exception to this treatment are event-firm size and creditworthiness, were we only consider the subsamples based on whether the event company is below/above industry average). Second, we test the null hypothesis of no difference between the distribution of CIASCs in the lower and the upper terciles using the Kruskall-Wallis test. For each conditioning variable we report the lower/upper tercile number of observations, the lower/upper tercile mean CIASC, the lower/upper tercile median CIASC, the lower/upper tercile Corrado Z-statistic, and the p-value of the Kruskall-Wallis (KW) test for the difference in the distribution between the CIASCs in the lower and the upper tercile of the stratified sample. The format that we choose to report the number of observations, mean CIASCs, and Corrado Z-statistics is:
(LOWER TERCILE VALUE OF STATISTIC / UPPER TERCILE VALUE OF STATISTIC).

Strat. Scheme	Statistics	Downgrades		Upgrades		Negative Reviews		Positive Reviews	
		$CASC_{event} > 0$	$CASC_{event} < 0$	$CASC_{event} > 0$	$CASC_{event} < 0$	$CASC_{event} > 0$	$CASC_{event} < 0$	$CASC_{event} > 0$	$CASC_{event} < 0$
Panel A: Size & Creditworthiness									
	#/#	**155 / 150**	81 / 92	70 / 73	69 / 66	**130 / 130**	38 / 49	20 / 29	19 / 38
Relative Size	Mean CIASC	**2.75 / 4.74**	-1.56 / -2.08	-1.39 / -0.71	-2.73 / -1.89	**3.63 / 4.79**	-0.33 / -0.82	1.53 / -1.18	-4.59 / -2.96
(Below/Above Industry	Corrado Z-stat	**[0.06 / 3.19]**	[-2.44 / -2.09]	[-0.56 / -0.31]	[-2.03 / -2.79]	**[1.53 / 1.98]**	[-0.6 / -0.8]	[1.07 / -0.47]	[-2.15 / -2.3]
Average Log Assets)	Kruskall-Wallis	**[[0.031]]**	[[1]]	[[0.41]]	[[0.69]]	**[[0.091]]**	[[0.331]]	[[0.434]]	[[0.531]]
	#/#	137 / 168	78 / 95	99 / 44	**83 / 52**	**104 / 156**	34 / 53	29 / 20	37 / 20
Event-Firm Creditworthiness	Mean CIASC	3.62 / 3.82	-5.11 / -5.84	-0.19 / -3.92	**-2.67 / -0.65**	**3.69 / 4.56**	-5.93 / -1.76	-1.19 / 1.56	-1.33 / -7.51
(Below/Above Industry Average)	Corrado Z-stat	[1.66 / 1.42]	[-1.55 / -2.82]	[-0.1 / -0.96]	**[-3.62 / -0.83]**	**[0.82 / 1.99]**	[-0.73 / -0.69]	[0.56 / -0.08]	[-2.23 / -2.47]
	Kruskall-Wallis	[[0.738]]	[[0.333]]	[[0.376]]	**[[0.049]]**	**[[0.086]]**	[[0.676]]	[[0.879]]	[[0.263]]
Panel B: Profitability & Market Valuation									
	#/#	94 / 92	54 / 52	45 / 44	41 / 40	83 / 81	27 / 26	14 / 14	17 / 16
Relative EBIT/Sales	Mean CIASC	4.12 / 2.02	-5.7 / -4.4	-3.09 / -1.06	-0.42 / -1.94	0.38 / 2.53	-1.13 / 5.72	2.87 / -0.69	-5.64 / -5.37
(Bottom/Top Tercile)	Corrado Z-stat	[1.51 / 1.19]	[-1.96 / -2.31]	[-0.58 / 0.07]	[-1.35 / -2.01]	[0.92 / 1.63]	[-0.29 / -0.1]	[0.61 / 0.03]	[-1.76 / -2.22]
	Kruskall-Wallis	[[0.499]]	[[0.887]]	[[0.968]]	[[0.93]]	[[0.616]]	[[0.428]]	[[0.292]]	[[0.226]]
	#/#	67 / 66	38 / 36	32 / 31	31 / 30	50 / 50	18 / 17	9 / 9	14 / 14
Relative ME/BE	Mean CIASC	6.48 / 7.76	-9.137 / 3.139	-2.1 / -2.34	-2.26 / -3.45	1.99 / 3.13	5.44 / -0.32	-0.03 / -2.39	-2.54 / -2.87
(Bottom/Top Tercile)	Corrado Z-stat	[2.31 / 0.86]	[-2.93 / -1.08]	[-0.99 / 0.43]	[-0.75 / -2.32]	[0.64 / -0.17]	[-0.66 / 0.04]	[-0.11 / 1.15]	[-2.41 / -1.46]
	Kruskall-Wallis	[[0.836]]	[[0.512]]	[[0.389]]	[[0.326]]	[[0.502]]	[[0.565]]	[[0.311]]	[[0.731]]
Panel C: Leverage									
	#/#	**94 / 92**	53 / 52	45 / 44	42 / 41	**85 / 83**	27 / 26	15 / 14	18 / 17
Relative Leverage - Long Term	Mean CIASC	**2.4 / 5.43**	-4.96 / -6.2	0.99 / -1.05	-1.28 / -2.3	**1.4 / 4.56**	-9.07 / 1.81	-0.63 / 0.44	-4.02 / 0.6
(Bottom/Top Tercile)	Corrado Z-stat	**[0.8 / 1.88]**	[-2.3 / -2.18]	[0.33 / -0.48]	[-2.08 / -2.59]	**[0.47 / 2.58]**	[-1.54 / 0.93]	[-0.22 / 0.71]	[-0.53 / -0.89]
	Kruskall-Wallis	**[[0.075]]**	[[0.944]]	[[0.257]]	[[0.627]]	**[[0.061]]**	[[0.298]]	[[0.453]]	[[0.125]]
	#/#	84 / 82	46 / 45	42 / 42	38 / 36	76 / 74	25 / 24	14 / 13	18 / 17
Relative Leverage - Short Term	Mean CIASC	4.93 / 2.02	-0.16 / -9.99	-2.28 / -0.48	-2.41 / -2.28	1.96 / 2.91	-4.39 / 3.46	-0.27 / 0.54	-5.85 / -1.88
(Bottom/Top Tercile)	Corrado Z-stat	[2.42 / -0.18]	[-0.53 / -3.38]	[-0.21 / -0.58]	[-1.54 / -2.17]	[1.28 / 1.3]	[-0.85 / -0.63]	[-0.08 / 0.55]	[-0.91 / -1.77]
	Kruskall-Wallis	[[0.325]]	[[0.295]]	[[0.711]]	[[0.877]]	[[0.176]]	[[0.313]]	[[0.975]]	[[0.593]]
Panel D: Liquidity									
	#/#	70 / 68	38 / 37	37 / 35	33 / 32	**69 / 66**	21 / 21	14 / 13	15 / 14
Relative Current Ratio	Mean CIASC	1.58 / 0.5	-6.87 / -1.95	-1.56 / 0.1	-2.79 / -3.63	**6.01 / -3.89**	4.82 / 8.69	-0.79 / 3.24	-2.09 / -3.54
(Bottom/Top Tercile)	Corrado Z-stat	[0.3 / -1.07]	[-2.05 / -1.1]	[0.19 / 0.44]	[-2.05 / -3.01]	**[2.11 / -1.17]**	[-1.06 / 0.71]	[-0.78 / 0.81]	[-1.78 / -0.93]
	Kruskall-Wallis	[[0.164]]	[[0.13]]	[[0.793]]	[[0.541]]	**[[0.013]]**	[[0.165]]	[[0.142]]	[[0.757]]

[1] The bald enteries in the table signify the event-type/stratification-scheme combinations for which the difference between the upper and lower tercile of the CIASC distribution is significant at the 10% significance level.

Table 2.7 – Industry Responses to the S&P Rating Announcements - Responses Stratified by Industry Characteristics. This table presents the [-1,1] cumulative industry abnormal spread changes (CIASC) stratified by the characteristics of the industry in which the event occurs. The CIASC calculation and the construction of industry portfolios is the same as before. We consider four broad classes of the industry characteristics: industry concentration, creditworthiness, cash-flow similarity & industry type (Panel A), profitability and market valuation (Panel B), leverage (Panel C), and liquidity (Panel D). Within each of these classes we condition the CIASCs on financial variables that correspond with a particular characteristic (the definitions of the financial variables used are provided in Table 2.5). This is done as follows. First, we split the sample of all CIASCs in terciles based on the values of the conditioning variable. Second, we test the null hypothesis of no difference between the distribution of CIASCs in the lower and the upper terciles using the Kruskall-Wallis test. For each conditioning variable we report the lower/upper tercile number of observations, the lower/upper tercile mean CIASC, the lower/upper tercile median CIASC, the lower/upper tercile Corrado Z-statistic, the difference (upper tercile minus lower tercile) in mean and median CIASCs, and the p-value of the Kruskall-Wallis (KW) test for the difference in the distribution between the CIASCs in the lower and the upper tercile of the stratified sample. The format that we choose to report the number of observations, mean CIASCs, and Corrado Z-statistics is:
(LOWER TERCILE VALUE OF STATISTIC / UPPER TERCILE VALUE OF STATISTIC).

Strat. Scheme	**Statistics**	**Downgrades**		**Upgrades**		**Negative Reviews**		**Positive Reviews**	
		$CASC_{event} > 0$	$CASC_{event} < 0$	$CASC_{event} > 0$	$CASC_{event} < 0$	$CASC_{event} > 0$	$CASC_{event} < 0$	$CASC_{event} > 0$	$CASC_{event} < 0$
Panel A: Industry Concentration, Creditworthiness, Cash-Flow Similarity & Industry Type									
	#/#	**75 / 78**	42 / 41	33 / 35	33 / 34	61 / 62	21 / 22	9 / 10	12 / 12
HHI	Mean CIASC	**-4.6 / 3.43**	-10.2 / 2.21	-2.16 / -0.89	-4.64 / -0.02	2.32 / 10.84	-34.22 / 6.65	0.64 / 1.28	2.69 / -2.92
	Corrado Z-stat	**[-0.93 / 1.5]**	[-1.52 / -1.36]	[-0.62 / -1.44]	[-0.98 / -1.11]	[1.55 / 1.51]	[-2.04 / 0.41]	[0.26 / 0.48]	[-0.31 / -1.5]
	Kruskall-Wallis	**[[0]]**	[[0.518]]	[[0.181]]	[[0.721]]	[[0.94]]	[[0.112]]	[[0.933]]	[[0.118]]
	#/#	**83 / 86**	**57 / 59**	32 / 32	**44 / 45**	**66 / 69**	29 / 29	9 / 9	19 / 19
Degree of Similarity Between	Mean CIASC	**1.66 / 8.68**	**-2.95 / -9.71**	-2.41 / -1.72	**-1.71 / -2.69**	**-0.59 / 9.12**	5.81 / -13.19	-2.53 / 0.97	-0.38 / -6.87
Event-Firm and Its Industry Peers	Corrado Z-stat	**[0.54 / 3.81]**	**[-1.36 / -2.88]**	[-0.89 / 0.86]	**[-1.7 / -2.68]**	**[0.3 / 2.8]**	[1.24 / -2.15]	[-0.06 / 0.82]	[-1.86 / -2.2]
	Kruskall-Wallis	**[[0.002]]**	**[[0.034]]**	[[0.423]]	**[[0.064]]**	**[[0.091]]**	[[0.118]]	[[0.215]]	[[0.247]]
	#/#	103 / 100	44 / 56	46 / 51	44 / 38	82 / 86	24 / 28	16 / 17	19 / 19
Average Industry	Mean CIASC	7.59 / 1.23	-10.93 / -1.33	-3.23 / -1.62	0.52 / -3.74	-6.36 / 5.59	-18.13 / 0.69	1.46 / -3.27	-6.51 / -2.06
Creditworthiness	Corrado Z-stat	[1.42 / 1.54]	[-1.29 / -1.73]	[-1.65 / 0.36]	[-0.74 / -1.92]	[1.02 / 2.12]	[-0.91 / -0.43]	[0.83 / -0.67]	[-1.92 / -2.25]
	Kruskall-Wallis	[[0.714]]	[[0.46]]	[[0.739]]	[[0.125]]	[[0.355]]	[[0.129]]	[[0.327]]	[[0.888]]
	#/#	**250 / 55**	141 / 32	121 / 22	**116 / 19**	218 / 42	69 / 18	47 / 2	51 / 6
Industry Type	Mean CIASC	**3.29 / 5.74**	-6.11 / -2.88	-1.06 / -2.85	**-1.94 / -1.57**	3.96 / 5.5	-5.55 / 5.32	-0.02 / -1.25	-3.68 / -1.93
(Non-Financial vs. Financial)	Corrado Z-stat	**[1.3 / 2.42]**	[-2.39 / -1.68]	[-0.18 / -1.27]	**[-2.93 / -1.66]**	[1.5 / 1.69]	[-1.32 / 0.52]	[0.51 / -0.58]	[-2.78 / -1.51]
	Kruskall-Wallis	**[[0.001]]**	[[0.403]]	[[0.712]]	**[[0.086]]**	[[0.209]]	[[0.205]]	[[0.266]]	[[0.917]]
Panel B: Profitability and Market Valuation									
	#/#	**102 / 103**	57 / 59	47 / 48	44 / 45	**86 / 88**	29 / 29	16 / 17	19 / 19
EBIT/Sales	Mean CIASC	**6.88 / 3.07**	-11.74 / -2.64	-3.02 / -1.51	-2.96 / -2.62	**-0.94 / 1.15**	-14.07 / 3.24	-2.12 / -0.46	-6.8 / -3.25
(Bottom/Top Tercile)	Corrado Z-stat	**[3.05 / 3.17]**	[-2.07 / -0.81]	[0.07 / -1.22]	[-2.13 / -2.34]	**[2.08 / 1.21]**	[-2.35 / -0.1]	[0.74 / -0.51]	[-2.25 / -1.8]
	Kruskall-Wallis	**[[0]]**	[[0.128]]	[[0.392]]	[[0.282]]	**[[0.094]]**	[[0.112]]	[[0.368]]	[[0.511]]

Table 2.7 continued

Strat. Scheme	Statistics	Downgrades		Upgrades		Negative Reviews		Positive Reviews	
		$CASC_{event} > 0$	$CASC_{event} < 0$	$CASC_{event} > 0$	$CASC_{event} < 0$	$CASC_{event} > 0$	$CASC_{event} < 0$	$CASC_{event} > 0$	$CASC_{event} < 0$
	#/#	**99 / 100**	57 / 59	49 / 48	44 / 45	87 / 88	29 / 27	16 / 16	19 / 18
ME/BE	Mean CIASC	**7.68 / 6.66**	-11.8 / 0.36	-3.82 / -0.51	-4.19 / -0.76	-5.59 / 0.23	0.01 / -0.27	1.05 / -0.19	-3.95 / -2.02
(Bottom/Top Tercile)	Corrado Z-stat	**[2.27 / 0.5]**	[-1.63 / -1.81]	[-2.13 / 1.11]	[-3.03 / -1.6]	[1.77 / 0.83]	[0.44 / -0.25]	[0.51 / 0.57]	[-2.63 / -1.35]
	Kruskall-Wallis	**[[0.004]]**	[[0.267]]	[[0.203]]	[[0.325]]	[[0.605]]	[[0.344]]	[[0.785]]	[[0.746]]
Panel C: Leverage									
	#/#	**100 / 102**	57 / 59	**47 / 47**	44 / 44	**86 / 88**	30 / 29	16 / 16	19 / 19
Leverage - Long Term	Mean CIASC	**2.43 / 13.53**	0.537 / -7.33	**-1.01 / -2.69**	-3.11 / -1.46	**0.2 / -2.93**	1.14 / -19.68	-0.04 / -0.72	-3.47 / -2.37
(Bottom/Top Tercile)	Corrado Z-stat	**[-0.337 / 2.33]**	[-1.66 / -2.04]	**[0.77 / -2.65]**	[-2.11 / -2.31]	**[-0.1 / 0.85]**	[0.06 / -0.97]	[-0.18 / 0.09]	[-2.14 / -1.07]
	Kruskall-Wallis	**[[0.002]]**	[[0.244]]	**[[0.016]]**	[[0.478]]	**[[0.052]]**	[[0.647]]	[[0.714]]	[[0.618]]
	#/#	101 / 104	**57 / 59**	**46 / 48**	44 / 45	**88 / 88**	28 / 29	16 / 16	19 / 19
Leverage - Short Term	Mean CIASC	0.67 / 3.24	**-2.02 / -8.23**	**-0.41 / -2.74**	-2.2 / -0.64	**8.27 / -7.87**	-3.49 / -14.29	0.58 / -1.45	-2.54 / -2.93
(Bottom/Top Tercile)	Corrado Z-stat	[0.31 / 1.69]	**[-1.48 / -3.48]**	**[1.01 / -1.69]**	[-1.92 / -1.51]	**[3.4 / 0.81]**	[-0.6 / 0]	[-0.17 / 0.37]	[-2.01 / -1.18]
	Kruskall-Wallis	[[0.423]]	**[[0.071]]**	**[[0.062]]**	[[0.718]]	**[[0.037]]**	[[0.319]]	[[0.792]]	[[0.814]]
Panel D: Liquidity									
	#/#	80 / 82	45 / 46	41 / 43	37 / 38	75 / 77	23 / 24	16 / 16	16 / 17
Current Ratio	Mean CIASC	0.65 / -4.38	-7.55 / -4.34	-2.69 / -2.2	0.23 / -2.84	4.95 / -10.32	-4.31 / -3.03	-1.44 / 0.45	1.74 / -6.74
(Bottom/Top Tercile)	Corrado Z-stat	[0.39 / 0.2]	[-0.86 / -1.84]	[0.21 / -0.19]	[-2.16 / -2.23]	[1.5 / 0.26]	[-0.24 / -0.67]	[0.92 / 0.1]	[-1.07 / -199]
	Kruskall-Wallis	[[0.356]]	[[0.786]]	[[0.475]]	[[0.61]]	[[0.34]]	[[0.851]]	[[0.524]]	[[0.356]]

[1] The bald enteries in the table signify the event-type/stratification-scheme combinations for which the difference between the upper and lower tercile of the CIASC distribution is significant at the 10% significance level.

Table 2.8 – Industry Responses to the S&P Rating Announcements - Alternative Stratification Schemes. This table presents the [-1,1] cumulative industry abnormal spread changes (CIASC) stratified by the characteristics of the industry in which the event occurs. The CIASC calculation and the construction of industry portfolios is the same as before. We condition the CIASCs on dummy variables that correspond to observation period, and the characteristics of the rating event (the definitions of the variables used are provided in Table 2.5). We test the null hypothesis of no difference between the distribution of CIASCs in the subsamples based on the value of the dummy using the Kruskall-Wallis test. For each dummy variable we report the 0/1-dummy value subsample number of observations, mean CIASC, median CIASC, Corrado Z-statistic, the difference (1-dummy valued subsample statistic less the 0-dummy valued subsample statistic) in mean and median CIASCs, and the p-value of the Kruskall-Wallis (KW) test for the difference in the distribution between the CIASCs in the two subsamples. The format that we choose to report the number of observations, mean CIASCs, and Corrado Z-statistics is:
(0-DUMMY VALUED STRATUM STATISTIC / 1-DUMMY VALUED STRATUM STATISTC).

Strat. Scheme	**Statistics**	**Downgrades**		**Upgrades**		**Negative Reviews**		**Positive Reviews**	
		$CASC_{event} > 0$	$CASC_{event} < 0$	$CASC_{event} > 0$	$CASC_{event} < 0$	$CASC_{event} > 0$	$CASC_{event} < 0$	$CASC_{event} > 0$	$CASC_{event} < 0$
	#/#	183 / 122	89 / 84	100 / 43	87 / 48	197 / 63	51 / 36	31 / 18	28 / 29
Before / After Lehmann Brother's	Mean CIASC	3.34 / 4.31	-2.38 / -8.83	-0.4 / -3.51	-0.82 / -3.83	4.48 / 3.36	-2.81 / -4.19	-1.25 / 1.96	-1.27 / -5.64
Bankruptcy Period	Corrado Z-stat	[0.53 / 2.67]	[-2.12 / -2.16]	[-0.14 / -0.9]	[-1.9 / -2.98]	[2.27 / 0.185]	[-0.7 / -0.62]	[-0.76 / 1.66]	[-2.24 / -2.35]
	Kruskall-Wallis	[[0.091]]	[[0.115]]	[[0.634]]	[[0.073]]	[[0.109]]	[[0.165]]	[[0.012]]	[[0.213]]
	#/#	292 / 13	164 / 9	139 / 4					
Severity of Rating Change	Mean CIASC	3.21 / 15.5	-5.37 / -8	-1.37 / -0.24					
(Magnitude <= 1/ > 1)	Corrado Z-stat	[2.43 / 0.65]	[-3.06 / 0.54]	[-0.58 / -0.42]					
	Kruskall-Wallis	[[0.429]]	[[0.761]]	[[0.941]]					
	#/#	261 / 44	158 / 15	125 / 18	118 / 17				
Rating Change Crosses	Mean CIASC	4.46 / -0.63	-5.31 / -7.63	-1.61 / 0.56	-1.44 / -5.02	**Not Applicable**			
Investment Grade - Junk Boundary	Corrado Z-stat	[2.3 / 0.07]	[-2.83 / -0.81]	[-0.72 / 0.06]	[-2.63 / -2.46]				
(No Cross / Cross)	Kruskall-Wallis	[[0.262]]	[[0.292]]	[[0.422]]	[[0.277]]				
	#/#	179 / 126	106 / 67	88 / 55	91 / 44				
Rating Change Across	Mean CIASC	4.7 / 2.35	-4.35 / -7.35	-0.91 / -2.02	-1.12 / -3.48				
Major Rating Classes	Corrado Z-stat	[3.58 / -0.54]	[-2.94 / -1.1]	[-0.49 / -0.4]	[-2.29 / -2.51]				
(No Cross / Cross)	Kruskall-Wallis	[[0.166]]	[[0.949]]	[[0.393]]	[[0.16]]				

[1] The bald enteries in the table signify the event-type/stratification-scheme combinations for which the difference between the upper and lower tercile of the CIASC distribution is significant at the 10% significance level.

3. Industry leverage (liquidity) may influence IIIT effect both in favor of contagion or competition. With respect to the former, if highly leveraged (illiquid) industries tend to be in a state of distress, they may perceive rating signals as the forecast for the resolution of their currently distressed state. This bodes in favor of contagious IIIT. On the other hand, high leverage (illiquidity) may make the industry peers see rating announcements as competitive signals, whereby a negative rating signal gives the industry a hope to profit from the failure of the event-firm (vice-versa for positive rating signals).

4. To the extent that the average industry creditworthiness measures the degree of industry distress our expectations with respect to its influence on IIIT effect are the same as in point (3).

5. We expect to observe stronger contagious IIIT effects in cases in which cash-flows of event-firms and their industry peers are closely related than in situations in which they are relatively unrelated.

Table 2.7 presents the results of stratification analysis based on industry characteristics. The principal observations are summarized below:

1. Industry concentration exhibits a statistically significant influence on industry responses only in the case of downgrades. For these, industries with high concentration exhibit stronger contagious response than industries with low concentration.

2. Degree of cash-flow similarity is positive related to the strength of contagious IIIT in the case of downgrades, negative reviews, and upgrades. The result is statistically significant only when abnormal spread-responses of event-firms have their predicted sign.

3. Industries with low average market valuations tend to precipitate stronger contagious IIIT effects than industries with high average market valuations.

4. Contagious IIIT following negative rating news is stronger in less profitable industries than in the more profitable ones.

5. Industry long term leverage is positively related with the strength of contagious IIIT in the case of rating downgrades.

6. Industry liquidity and average industry credit quality exhibit no clear-cut influence on industry responses to rating events.

7. Responses of financial corporations to negative rating signals tend to be significantly more contagious than the responses of non-financial corporations. There is no statistically significant difference between the two in the case of positive rating signals.

Characteristics of the Rating Event

Strength and direction of IIIT effects may depend on the nature and the situational context of a rating signal. For example, it might be the case that investors holding industry portfolios become more perceptive to individual rating announcements during bad economic times, when counterparty dependencies among firms become a matter of higher concern. Likewise, investors' responses to rating signals are likely to be influenced by severity of rating signals, measured by the magnitude of a rating change. In this section we investigate the role played by such factors. In particular, we study whether IIIIT effects differ across: (a) one-notch and multiple-notch rating changes, (b) rating changes that push an event-company over investment/speculative-class boundary, (c) rating changes that push an event-company over the major-rating classes[20], and (d) rating signals that occur in periods before and after Lehman Brother's Default. Points (a), (b), and (c) all capture severity of a rating signal. We expect to observe stronger contagious and competitive IIIT effects when the rating signals are more severe. With respect to (d) we hypothesize the contagious IIIT effects to be of larger magnitude during the financial crisis period following the Lehman's default. Tests of the hypotheses are presented in Table 2.8. Severity of rating change, as measured by (a), (b), and (c) has no statistically significant influence on the distribution of IIIT effects. We note, however, that negative rating signals tend to be significantly more contagious during the post-Lehman period.

2.7.3 Multivariate Regression Analysis

The stratification approach undertaken in the previous sections faces two major disadvantages. First is that it essentially loses information by only considering terciles of the conditioning variable distribution. Second, it fails to control for correlations

[20] We define 'major rating classes' as the letter-only ratings assigned by the agencies, i.e. rating without +/- modifiers in the case of S&P and Fitch, and rating without number modifiers in the case of Moody's.

between different determinants, which may give rise to spuriously significant influence of certain determinants[21]. We mitigate these concerns by studying IIIT effects in the multivariate regression setting. If IIIT effects were uniform across event-firm, industry, and event characteristic, we could identify their direction and magnitude by estimating the following specification:

$$CIASC_i = \gamma_0 + \gamma_1 CASC_i + \eta_i, \tag{2.13}$$

where $CIASC_i$ (resp. $CASC_i$) is an industry (resp. event-firm) spread response to event i. In this case the positive (negative) estimate for γ_1 would indicate the contagious (competitive) IIIT effect.

Motivated by the stratification analysis from before, we expect that contagious/competitive IIIT effects depend on k additional factors, captured by $k \times 1$ vector Z_i, where i denotes a cross-sectional unit of observation. Put differently, we expect γ_1 in (2.13) to be a function of Z_i.

We posit the following specification for the conditional industry peers response to the rating event i:

$$CIASC_i = \theta_0 + \theta_1\ CASC_i + \theta_2'\ Z_i + \theta_3'\ CASC_i * Z_i + \epsilon_i, \tag{2.14}$$

where θ_2 and θ_3 are $k \times 1$ vectors of coefficients, and where the apostrophe denotes the transpose. From (2.14) one can extract the value of conditional IIIT effects by considering the marginal effects of $CASC_i$:

$$IIIT(Z_i) = \frac{\partial CIASC_i}{\partial CASC_i} = \theta_1 + \theta_3'\ Z_i. \tag{2.15}$$

Let $\hat{\theta}_1$ and $\hat{\theta}_2$ be the estimates of θ_1 and θ_2. The variance of the estimated IIIT is then:

$$Var(\widehat{IIIT} \mid Z_i) = Var(\hat{\theta}_1) + Var(\hat{\theta}_3'\ Z_i) + 2\ Cov(\hat{\theta}_1, \hat{\theta}_3'\ Z_i). \tag{2.16}$$

Specification in (2.14) is estimated by OLS, using a heteroskedasticity-robust variance estimator. Estimators in (2.15) and (2.16) are easily computed using standard econometric software.

One of the challenges in selecting a covariate vector Z_i is that interaction terms in (2.15) lead to a high degree of multicollinearity, which quickly inflates the variance of estimators. To limit the impact of multicollinearity, we only include variables whose

[21] Despite these problems, stratification analysis is a standard part of informational contagion market efficiency studies.

individual correlation (not accounting for interactions) coefficients do not exceed the value 0.4.

Our final selection of covariates reflects the trade-off between keeping the model reasonably small (so as to limit the multicollinearity) and including (potentially) economically important variables. We judge the potential economical importance of the included covariates by the significance of their influence found in the stratification analysis. We note that creditworthiness, especially at the industry level, tends to be highly correlated with leverage, profitability and liquidity measures. In particular, high credit ratings tend to be assigned to entities (and industries) that are relatively big, profitable, liquid, and have a relatively low leverage. For this reason, we treat event-firm and industry creditworthiness as a summary measure for the other performance dimensions.

Our final selection of Z_i includes:

1. Relative event-firm size measured as a ratio of event-firm and median industry total book assets.

2. Size of industry peers, measured as the industry median of log total assets.

3. Correlation between the equity returns of event-firm and of industry peer portfolio. This proxies for the cash-flow similarity between the event-firm and its industry peers (e.g. Xu et al. (2006), Lang and Stulz (1992)).

4. Relative event-firm long-term leverage.

5. Relative event-firm creditworthiness.

6. Average industry creditworthiness.

Due to interactions, raw regression coefficients in equation 2.14 are difficult to interpret economically, so we present them in the appendix (Table 2.12). Instead, Figures 2.9, and 2.10 present the plots of marginal effects (see equation 2.15) for various levels of the conditioning variables together with 95% confidence intervals. In each of the plots, the non-varying covariates are evaluated at their sample means. The main observations are as follows:

1. The magnitude of marginal effects is between -0.2 and 0.4, suggesting that changes in industry abnormal spreads on average amount to up to 40% of the event-firm abnormal spread change.

Figure 2.9 – Conditional IIIT Effects - Rating Changes. The exhibit presents conditional marginal industry responses (see equation (15)) to downgrades and upgrades together with 95% confidence intervals. Marginal responses are computed from specification in Table 2.12 and are evaluated at the sample averages of the "non-varying" covariates. We condition the marginal responses on (a) the relative-event firm size (event-firm total assets over median industry total assets), (b) median size of industry-peers (industry median of log total assets), (c) event-firm and industry cash-flow similarity (measured as a correlation between the equity returns of the event firm and the industry portfolio during 200 days before the event), (d) relative event-firm creditworthiness where values above/below zero correspond to above/below average event-firm creditworthiness, (e) industry creditworthiness where higher values correspond to relatively higher average industry ratings, (f) relative event-firm leverage where values above/below zero correspond to above/below average event-firm leverage. Confidence intervals are based on heteroskedasticity-adjusted standard errors.

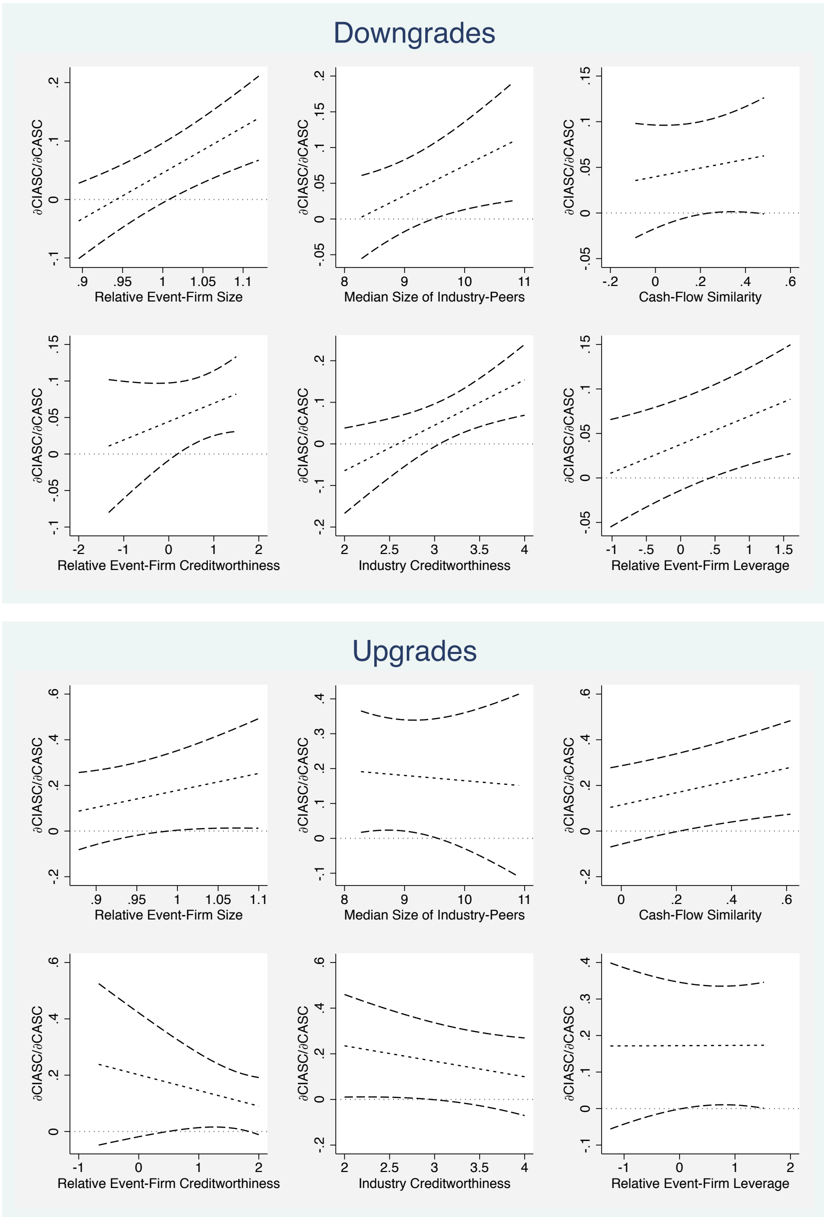
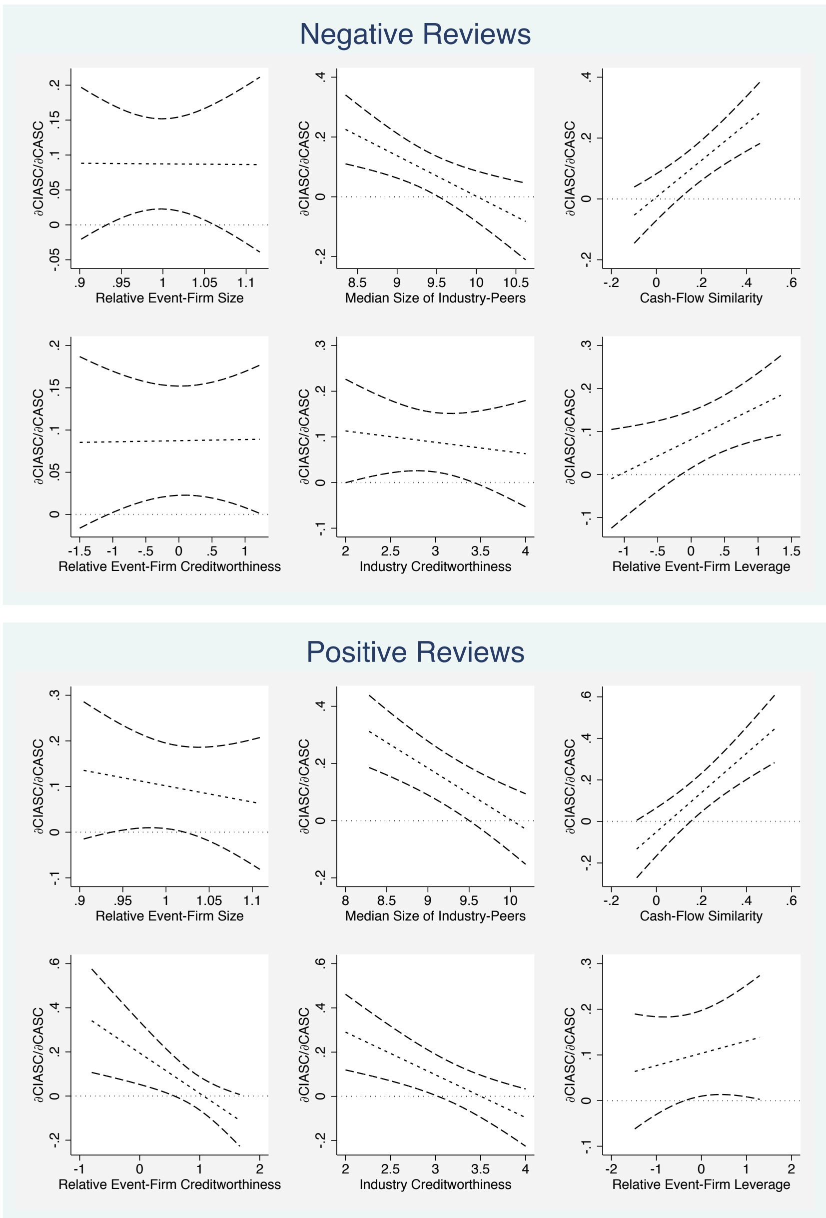


Figure 2.10 – Conditional IIIT Effects - Rating Reviews. The exhibit presents conditional marginal industry responses (see equation (15)) to reviews for downgrades and upgrades together with 95% confidence intervals. Marginal responses are computed from specification in Table 2.12 and are evaluated at the sample averages of the "non-varying" covariates. We condition the marginal responses on (a) the relative-event firm size (event-firm total assets over median industry total assets), (b) median size of industry-peers (industry median of log total assets), (c) event-firm and industry cash-flow similarity (measured as a correlation between the equity returns of the event firm and the industry portfolio during 200 days before the event), (d) relative event-firm creditworthiness where values above/below zero correspond to above/below average event-firm creditworthiness, (e) industry creditworthiness where higher values correspond to relatively higher average industry ratings, (f) relative event-firm leverage where values above/below zero correspond to above/below average event-firm leverage. Confidence intervals are based on heteroskedasticity-adjusted standard errors.



2. In the case of downgrades, the strength of contagious IIIT effects is positively related to event-firm size. This suggests that industry investors perceive downgrades as a more serious indicator of worsening industry prospects when the downgraded entity is large, which is in line with the economic intuition. The relationship fails to hold for other types of events, in particular for rating reviews.

3. Industry responses to downgrades tend to be more contagious in industries with big firms (in absolute terms) than the ones with small firms. For negative/positive reviews we observe the opposite: contagious industry responses tend to be stronger in small-firm industries.

4. The degree of cash-flow similarity between the event-firm and its industry, measured by the correlation between the event-firm and industry portfolio stock returns, is positively associated with the strength of contagious response to all four types of events. The positive relation is particularly strong in the case of rating reviews. This observation concurs with the economic intuition, which says that industries with high cash flow similarities should display higher degree of co-movement following rating events.

5. Event-firms with above-average credit quality precipitate stronger contagious IIIT following downgrades than the below-average credit quality firms. This suggests that downgrades of above-average credit quality corporations are deemed to be a more serious indicator of worsening industry creditworthiness.

6. Industries with high average credit quality tend to display stronger contagious IIIT in the case of downgrades. Oppositely, positive rating news are significantly more contagious when they occur in the relatively less creditworthy industries. Taken together, these observations imply that rating announcements carry more industry-relevant information when they come as a contrast to the current credit rating of an event-firm or an industry (i.e. negative (positive) rating news for companies/industries with high (low) credit ratings).

7. Relative event-firm leverage is positively related to the strength of contagious IIIT effects especially in the case of negative rating signals. This suggests that negative rating announcements associated with highly leveraged firms carry more industry-level information.

Table 2.11 presents the marginal peer responses evaluated at the sample averages of each of the covariates. For negative rating events the IIIT effects are found to be contagious and statistically significant at the 5% significance level. This is in roughly in line with the univariate results presented in Table 2.4[22].The magnitude of IIIT effects is about 6% of the event-firm response, both for positive and negative rating announcements. While this number might appear to be relatively small, one should note that the magnitude found here concurs with the recent equity-based study of Jorion and Zhang (2010) who find that for downgrades the peer equity response is about 4% of the event-firm equity response[23].

Table 2.11 – Marginal Industry Responses. The table presents marginal industry responses (see equation (15)) to four types of rating events. Marginal responses are computed from specification in Table 2.12 and are evaluated at the sample averages of the corresponding covariates.

			Marginal Peer Response ($\frac{\partial CIASC}{\partial CASC}$)		
Event Type	# of Obs.	Average Event Firm Response (in b.p.)	Relative	Absolute (in b.p.)	p-value
Downgrades	389	27.7200	0.0534**	1.4802**	0.0330
Upgrades	215	-5.3810	0.0424	-0.2283	0.1730
Negative Reviews	275	23.5569	0.0674***	1.5877***	0.0010
Positive Reviews	78	-18.6286	0.0672	-1.2518	0.1010

[1] *, **, and *** denote significance at 10, 5 and 1% level, respectively.

2.8 Conclusions

The aim of this chapter is to empirically test for the presence of intra-industry informational transfers (IIIT) induced by rating signals in the markets for corporate credit risk. In particular, we study the intra-industry CDS spread responses to credit rating announcements made by S&P, Moody's, and Fitch between January 2003 and March 2011. We find statistically and economically significant industry spread responses to the announcements made by S&P, and only marginally significant and insignificant industry spread responses to the rating signals of Moody's and Fitch, respectively. This suggests that S&P announcements contain the largest component of the industry-wide information. In the case of S&P, we observe strong evidence in favor of contagious IIIT, implying that on the day of announcement the industry

[22]Discrepancies in results between results in Table 2.4 and Table 2.11 might stem from: (1) different estimation samples (results in Table 2.11 necessitate the presence of accounting data) and (2) different estimation methods (non-parametric vs. parametric).

[23]Jorion and Zhang (2010) find the event-firm (industry) response to downgrades to be 1.7% (0.08%), which implies the relative industry response of 0.04.

abnormal spreads tend to move in the same direction as the event-firm spreads. This finding holds across all four types of rating events, and in particular for the cases in which the event-firm spread reaction has its predicted sign (positive (negative) spread change in the case of negative (positive) rating news). The magnitude of the industry peer reaction (to S&P announcements) is found to be about 6% of the event-firm abnormal spread change.

Stratification and multivariate regression analyses reveal a rich pattern of IIIT behavior across several event-firm, event, and industry characteristics. For negative rating events, contagious IIIT effects tend to be stronger when event-companies: (a) are relatively large (only in the case of downgrades), (b) come from industries with large industry peers, (c) have high degree of cash-flow similarity with their industry peers, (d) are highly leveraged, (e) have higher than industry-average credit rating before the event, and (f) come from relatively credit-worthy industries. For positive rating events, the contagious IIIT effects tend to increase with: (a) industry-peer cash flow similarity, and (b) degree of financial distress, characterized by below-average event-firm credit quality and low average industry credit quality.

The principal finding of this chapter is that S&P's rating signals, and negative signals in particular, elicit contagious response in the abnormal spreads of the event-firm's industry peers. One possible explanation of this finding, cast in terms of information content of rating signals, is that rating announcements deliver new information on the future trajectory of the industry component of corporate credit quality. For this argument to hold, rating agencies should have a comparative advantage (relative to individual investors) in determining the dynamics and evolution of industry creditworthiness. Rating agency superiority in identifying industry trends might stem from scope economies in information gathering. When a rating agency produces rating information for more than one company from a given industry, it acquires a unique vantage point, from which it might be able to access and compare the individual firms' strategies and investment plans (some of which is an information of non-public character). This, in turn, might allow the agency to produce superior forecasts on the evolution of the industry component of credit risk.

The importance of industry analysis in the credit rating process bodes in favor of the information-based explanation. Sector analysis provides one of the main inputs in the production of a final rating decision. Indeed, rating agencies explicitly acknowledge that industry assessment sets an upper bound for the ratings that firms can aspire for (see 2.2). These observations suggest that a substantial portion of rating agencies' information gathering activity pertains to the assessment of the industry component of credit risk, which explains why rating decisions may be informative for wider investor communities.

Appendix

2.A Corrado Ranksum Test

In what follows, we briefly outline the computation of the Corrado Ranksum Test. For more details, see Corrado (1989). Let N and E denote the sets of days in pre-announcement and announcement windows, respectively. Denote the number of days in the sets N and E by n and e, respectively. Further, let K_{jt} be the rank of abnormal spread of entity j at time t, where rank of one represent the smallest abnormal spread in the sample of $n+e$ abnormal spreads of entity j. Let mean and median rank be given as:

$$\tilde{K} = \frac{n+e+1}{2}. \tag{2.17}$$

The Corrado Ranksum Z-statistic is given as:

$$z_{corrado} = E^{\frac{1}{2}} \left\{ \frac{\bar{K}_* - \tilde{K}}{\sqrt{\sum_{t \in N \cup E} \frac{(\bar{K}_t - \tilde{K})^2}{n+e}}} \right\}, \tag{2.18}$$

where $\bar{K}_* = \frac{1}{e} \sum_{t \in E} \frac{1}{J} \sum_{j+1}^{J} K_{jt}$, $\bar{K}_t = \frac{1}{J} \sum_{j=1}^{J} K_{jt}$, and J is the number of entities. The test rejects the null of no abnormal performance when the average rank observed in the sample significantly deviates from the expected rank $\tilde{K}$ (under no abnormal performance). $z_{corrado}$ is approximately standard normally distributed under the null of no abnormal performance.

2.B Multivariate Regression in Section 1.7.3

Table 2.12 – Industry Announcement Window Responses Stratified by Event-Firm Characteristics

	Downgrades	Upgrades	Neg. Reviews	Pos. Reviews
CASC_EF	-1.456***	-0.245	1.317*	2.560**
	(-3.281)	(-0.307)	-1.894	-2.585
RELATIVE_SIZE_EF	-18.57	7.325	-2.141	-28.94
	(-0.896)	-0.691	(-0.0889)	(-1.446)
SIZE_IND	-5.277***	-0.444	-0.223	-1.714
	(-2.747)	(-0.407)	(-0.105)	(-1.020)
CORR	2.029	4.087	8.112	0.211
	-0.272	-1.243	-0.96	-0.038
RELATIVE_CREDITWORTH_EF	0.311	-0.11	-0.447	-3.245**
	-0.171	(-0.112)	(-0.184)	(-2.162)
CREDITWORTH_IND	-2.562	1.046	-1.465	-2.29
	(-0.906)	-0.693	(-0.446)	(-1.152)
RELATIVE_LEVERAGE_EF	-2.043	0.716	-2.801	-0.98
	(-1.122)	-0.873	(-1.341)	(-0.692)
CASC_EF * RELATIVE_SIZE_EF	0.785***	0.746	-0.00898	-0.355
	-3.238	-1.145	(-0.0164)	(-0.526)
CASC_EF * SIZE_IND	0.0419*	-0.015	-0.135**	-0.180***
	-1.84	(-0.235)	(-2.484)	(-3.316)
CASC_EF * CORR	0.0474	0.268*	0.603***	0.944***
	-0.6	-1.914	-3.897	-4.062
CASC_EF * RELATIVE_CREDITWORTH_EF	0.0251	-0.0556	0.00136	-0.183**
	-1.111	(-0.846)	-0.0444	(-2.402)
CASC_EF * CREDITWORTH_IND	0.109**	-0.0678	-0.0249	-0.193***
	-2.297	(-1.059)	(-0.436)	(-2.667)
CASC_EF * RELATIVE_LEVERAGE_EF	0.0318**	0.00068	0.0767**	0.0268
	-2.104	-0.0144	-1.989	-0.673
Constant	72.24**	-7.424	9.127	51.77*
	-2.382	(-0.415)	-0.266	-1.872
Observations	391	215	275	78
Adjusted R-squared	0.113	0.071	0.238	0.502

[1] t-statistics are reported in parenthesis and are based on heteroskedesticity-adjusted standard errors.
[2] *, **, and *** denote significance at 10, 5 and 1% level, respectively.

Post-Scriptum to Chapter 2

The aim of this section is to outline some of the directions that the literature on the information content of credit ratings has taken since the publication of this chapter in the Autumn of 2013 (see Cizel, 2013).

Informational impact of corporate credit rating news

Finnerty et al. (2013) examine the impact of credit rating information on CDS spreads for the global sample of corporate entities. They begin by showing that both positive and negative rating news generate statistically significant pricing impact on CDS spreads of the rated entity. The main contribution of the paper is in its findings on the asymmetric impact of positive and negative rating events. In particular, they examine the extent to which pre-event CDS changes anticipate the rating events and document an asymmetry in the anticipation effect: negative rating news tend to be better anticipated by the CDS markets than the negative rating news.

Wengner et al. (2015) follow Cizel (2013) by studying the IIIT effects due credit rating announcements by the S&P for the global set of corporate entities. The results confirm the presence of IIIT effects both for positive and for negative rating events. The results also indicate the economic magnitude of IIIT effects increased following the onset of the GFC.

Informational impact of sovereign credit rating news.

With the backdrop of the sovereign debt crisis in Europe that was taking place (with fluctuating intensity) during the period of 2009-15, the literature has also looked at the information content of the sovereign credit ratings. Contributions in this area include Kremser et al. (2013) and Caselli et al. (2016). Kremser et al. (2013), who study pricing impact in the context of sovereign CDS, shows that the low-quality obligors' CDS spreads display stronger sensitivity to rating news than is the case for the high-quality obligors. Safari and Ariff (2015) examine the impact of sovereign credit rating changes in EMEs on the countries' stock, bond, and future markets. They show that the effect of rating events is asymmetric: most markets respond only to rating downgrades but not to upgrades. Finally, Caselli et al. (2016) study the spillover effects of sovereign rating changes on equity prices of the European banks during the pre- and post-GFC period. They find evidence of spillover effects for the negative rating news, but not for the positive.

CHAPTER 3

Anatomy of Bank Distress: The Information Content of Accounting Fundamentals Within and Across Countries[1]

3.1 Introduction

The recent global financial crisis that began in the dysfunctional U.S. residential mortgage market in late 2007, and quickly spread to the rest of the global financial system, has produced an unprecedented number of bank failures, on par only with the Great Depression era's financial meltdown. During the period of 2007-12, about half of the U.S. and one third of the Western European commercial banking assets belonged to banks that were either closed or experienced some form of government assistance, typically via taxpayer-financed recapitalizations (see Table 3.2). The sheer extent of the financial distress has kindled a substantial research effort devoted to examining causes, consequences, and government responses to the recent banking crisis. Laeven (2011) and Gorton and Metrick (2012) provide an extensive review of some of the recent work in this area.

A growing number of regulatory reports and academic studies has recently questioned the comparability and risk-sensitivity of bank accounting disclosure

[1]This chapter is based on Cizel et al. (2014), co-authored with Professor Edward I. Altman (*New York University, Stern School of Business*) and Professor Herbert A. Rijken (*Vrije Universiteit Amsterdam*).

during the financial crisis (see Mariathasan and Merrouche, 2014; BCBS, 2013; Le Lesle and Avramova, 2012). The main concern common to these studies is that a substantial accounting discretion of banks may have contributed to systematic reporting biases by weak institutions and thus deteriorated the comparability of reported accounting signals between banks and across countries. We contribute to this literature by (1) providing a comprehensive cross-country analysis of the information content of accounting fundamentals in anticipating bank distress in Western Europe and the U.S. during the period 2007-12, and (2) by studying the nexus between the informativeness of bank accounting and the national bank disclosure requirements (and their enforcement).

To set the stage, we construct a comprehensive database of bank distress events, drawing on a number of publicly available sources. The range of events covered by our database includes bank liquidations, bankruptcies, regulatory receiverships, distressed mergers, distressed dissolutions, and open-bank assistance, typically in the form of government recapitalization of ailing banks. We categorize events into two broad groups of bank resolution: (1) *bank closures*, corresponding to resolutions in which distressed banks cease to exist as independent entities, and (2) *open-bank resolutions*, in which banks are allowed to continue operating with the assistance of a government bail-out.

We analyze the drivers of bank distress by modelling the two competing groups of distressed bank resolutions in a logistic regression framework. In our benchmark specifications we test for a number of bank-specific variables, including size, regulatory capital, asset quality, liquidity, franchise, or charter value[2], and funding costs. We find that both closures and open-bank resolutions tend to occur in severely undercapitalized banks with poor asset quality (measured by the reported risk-weighted assets and loan impairments), low charter values (proxied by the net-interest spread), and high funding costs.

Next, we conduct an in-depth examination of the information content of the accounting fundamentals by studying the ability of accounting numbers (1) to identify distressed banks within individual countries, and (2) to explain the aggregate incidence of bank distress during 2007-10. We show that predictions generated by accounting-based models display a substantial cross-country variation in the bank distress classification performance. We also demonstrate that the values of accounting

[2]By bank charter value we refer to the sum of positive NPV projects within the bank. Literature typically attributes positive bank charter values to the presence of financial market frictions, such as search costs, that make banking industry less-than-perfectly competitive and allow banks to generate monopolistic rents.

fundamentals, aggregated at the country level during the pre-crisis years of 2006 and 2007, fail to explain the 2007-10 aggregate incidence of bank distress across countries.

The final part of the paper examines the extent to which the observed cross-country variations in the informativeness of bank accounting are explained by differences in the national disclosure standards and their enforcement by the regulators. We measure the national bank disclosure quality by a set of indices from the database of Barth et al. (2013), who compile a selection of more than 50 different proxies from the Quadrennial World Bank surveys covering 180 countries since 1999. We begin by showing that countries in our sample exhibit a substantial variation in the proxies of disclosure quality. Next, we show that the informativeness of accounting fundamentals in the cross section of banks in a given country-year positively correlates with the quality of accounting standards and the stringency of their enforcement. In particular, accounting signals of bank distress tend to be stronger in countries with strong disclosure laws or with more stringent enforcement of the existing laws. We also demonstrate that the disclosure-quality/informativeness nexus holds when looking at the time series movements in accounting fundamentals at the level of distressed banks prior to the distress event.

Our paper relates to three strands of banking and accounting literature. First, we contribute to the extensive empirical research on the determinants and prediction of bank failures that began with the contributions of Sinkey (1975) and Altman (1977). Most of this research has focused on analyzing bank closures in the U.S., primarily due to the abundance of bank credit events, and the relatively consistent and detailed coverage of bank accounting information[3]. More recently, several studies have also studied bank distress in East Asia (Bongini et al., 2001; Arena, 2008; Wong et al., 2010), Latin America (Molina, 2002; Arena, 2008) and Europe (Betz et al., 2014; Cipollini and Fiordelisi, 2012; Cihak and Poghosyan, 2009). We expand this literature by studying bank distress in an international context, which allows us to assess the informativeness of bank accounting across different countries. Our unique database of bank distress events also permits us to discriminate between different types of bank resolution.

Second, our study relates to the accounting literature on firm disclosure. The extensive reviews of theoretical and empirical contributions in this literature can be

[3]All chartered U.S. banks are required to disclose their financial information to regulators in the form of Call Reports. Call reports are filed on a quarterly basis, and contain a number of pre-specified balance-sheet and income statement items, in addition to other information required by regulators. The Call Reports are publicly available via the web page of the Federal Deposit Insurance Corporation (FDIC).

found in Healy and Palepu (2001) and Beyer et al. (2010). Most of the empirical literature in this area measures the information content of accounting signals with the reference to the impact that accounting signals have on firms' security prices. Conversely, papers like Altman et al. (2010) assess the information content of different types of market prices, by studying their ability to anticipate firm defaults. Our paper combines elements of both approaches and proposes a set of new measures of the information content of accounting fundamentals, all of which correspond to the ability of the accounting fundamentals to anticipate firm distress. As such, our measures are applicable not only to listed but also to private companies.

Finally, we contribute to the literature on the nexus between the accounting disclosure environment and the informativeness of reported financial statements. In addressing this issue, the paper most similar to ours is Beaver et al. (2012), which examines the impact of managerial financial reporting discretion on the effectiveness of accounting data in predicting *non-financial firm* bankruptcies. They find that the predictive power of accounting-based bankruptcy models deteriorates significantly with increasing levels of managerial reporting discretion, where reporting discretion is proxied by earning restatements, and the impact of discretionary accruals. In contrast to their study, we examine informativeness of bank accounting measure by exploiting substantial cross-country variation in bank regulation on disclosure and monitoring standards.

Given that investors and regulators typically learn about banks' financial condition from the banks' public disclosures, our results have clear implications for bank disclosure regulation. The evidence in this paper supports the oft-voiced belief that excessive flexibility in financial reporting undermines the ability of accounting signals to accurately capture the underlying financial health of banks. Obliqueness of the distressed bank's accounting signals makes such information less useful for investors and regulators. One of the implications of this conclusion is that the information content of accounting fundamentals, at least with respect to the identification of distressed banks, might be improved by increased stringency of bank disclosure laws and their enforcement.

The plan of the paper is as follows. We begin by describing the construction of the database on bank distress during the recent crisis and outlining our sample of banks (Section 3.2). Sections 3.3 models the within-country variation in bank distress, and Section 3.4 studies the variation in effectiveness of accounting fundamentals across countries. Section 3.5 examines the correspondence between accounting information and the quality of bank disclosure standards and their enforcement by the regulators.

Section 3.6 concludes by providing a discussion of our findings and potential policy implications.

Table 3.1 – Literature on the Bank Distress Prediction

Paper	Focus	Main Findings
Meyer and Pifer (1970)	Prediction of US bank failures via accounting-based predictors.	Financial variables can discriminate between failed and surviving banks up to two years in advance.
Sinkey (1975)	Prediction of US bank failures via accounting-based predictors.	Financial measures related to asset composition, loan characteristics, capital adequacy, efficiency, and profitability are good discriminators between the groups of healthy and unhealthy banks.
Altman (1977)	Study of the financial distress in the US savings and loans industry.	Quadratic discriminant models based on accounting variables exhibit high predictive accuracy up to three semi annual periods in advance.
Martin (1977)	Prediction of US bank failures via accounting-based predictors.	Asset quality and capital adequacy variables are the key predictors of financial distress.
Lane et al. (1986)	Cox proportional hazard model of US bank defaults. Benchmarking of Cox model predictive performance to alternative classification methodologies. Accounting-based covariates.	Classification accuracy of Cox model similar to discriminant analysis.
Demirguc-Kunt (1989)	Review of the empirical literature on the US bank failures during the 1980s.	CAMEL variables are found to be good predictors of bank failures with relative consistency across different studies.
Looney et al. (1989)	Analysis of Type I and Type II errors in bank failure prediction models.	
Thomson (1991)	Analysis of the US bank failures during the S\&L crisis in the 1980s.	CAMEL variables exhibit good in sample and out-of-sample predictive performance.
Tam and Kiang (1992)	Estimate a neural network model of the US bank failures, and compare the accuracy of the model with discriminant analysis, and logistic regression.	Neural networks provide marginally better predictive performance than the alternative methods.
Wheelock and Wilson (1995)	Study of the timing of US bank failures in the early twentieth century via hazard-based methods.	The membership in the deposit insurance system increased probability of bank failure.
Demirguc-Kunt and Detragiache (2000)	Prediction of international banking crises, via the macroeconomic predictors.	GDP growth, real interest rate, inflation, and credit growth serve as strong predictors of banking crises.

Table 3.1 continued on next page

Table 3.1 continued from previous page

Paper	Focus	Main Findings
Wheelock and Wilson (2000)	Competing risks hazard framework to model failures and acquisitions of the US banks.	Inefficiency increases the risk of failure while reducing the probability of the acquisition.
Bongini et al (2001)	Analysis of bank failures during the 1997-1999 East Bongini et al. (2001)	Among CAMEL variables, bank asset growth and returns on assets serve as particularly good predictors of bank failure. Governance variables improve the predictive power of the model.
Sarkar and Sriram (2001)	Estimation of Bayesian models for predicting bank failures.	Bayesian modeling approach yields accurate predictions of bank default.
Molina (2002)	Prediction of bank failures during the Venezuelan banking crisis.	Bank profitability and bank holdings of domestic government bonds are the key discriminants of bank distress.
DeYoung (2003)	Analysis of the failures of the newly chartered banks in the US between 1980 and 1985.	The new bank failure is more sensitive to adverse environmental conditions.
Distinguin et al. (2006)	Analysis of the ability of stock market data to predict bank financial distress.	Market-based indictors improve the predictability of accounting based models, mainly for the banks with larger fraction of their liabilities.
Curry et al. (2007)	Analysis of the ability of stock market data to predict bank financial distress.	Market data improves the out-of-sample performance of the accounting based models, especially at the short forecasting horizons.
Arena (2008)	Bank-level analysis of bank failures in Latin America and East Asia during the 1990s.	Bank-level fundamentals significantly affect the likelihood of bank failures. Important role of macroeconomic variables.
Aschcraft (2008)	An impact of bank holding companies on the distress of their subsidiaries	Affiliation with BHC reduces subsidiaries' likelihood of distress.
Cihak and Poghosyan (2009)	Analysis of the distress of European banks from mid 1990s to 2008.	Capitalization, asset quality and profitability are the most important leading indicators of bank distress.
Mannasoo and Mayes (2009)	Analysis of bank distress in Eastern Europe transition economies, using the discrete time survival model.	Important role of traditional CAMELS factors in predicting distress. Macroeconomic variables improve the accounting-based model performance.
Aubuchon and Wheelock (2010)	Analysis of the US bank failures during 2007-2010 crisis.	Geographical patterns of the recent bank failures similar to the past banking failures in the US.
Wong et al. (2010)	Prediction of bank distress in EMEAP economies (Executives Meeting of East Asia Pacific Central Banks)	Macroeconomic fundamentals, currency crisis vulnerability, bank-specific credit risk, and health of the non-financial sector found to be strong leading indicators of banking distress.
Jin et al. (2011)	Analyzes the ability of accounting and audit quality variables to predict bank distress in the US.	Auditor type, audition industry specialization, and asset quality found to be important predictors of bank distress.

Table 3.1 continued on next page

Table 3.1 continued from previous page

Paper	Focus	Main Findings
Ng and Roychowdhury (2011)	Analyzes whether loan loss reserves predict bank failures, and whether loan loss reserves behave like bank capital in terms of discriminating between distressed and healthy institutions.	Finds that loan loss reserves are positively associated with bank distress. Distress risk concentrated in cases in which the addition of loan loss reserves to regulatory capital significantly improves a bank's capital ratio.
Cipollini and Fiordelisi (2012)	Analysis of bank distress in Europe. Distress defined as the event in which bank capital falls below a threshold.	Liquidity risk, credit risk, and bank market power are the most important predictors of bank distress.
Cole and White (2012)	Analysis of commercial bank failures in the US during 2007-2010.	CAMEL variables that explained the bank failures during the S&L crisis in the US, also explain the failures during the recent crisis.
Betz et al. (2014)	Analysis of bank distress in Europe.	CAMEL variables complemented by macroeconomic indicators yield good out-of-sample predictions of distress.
Maghyereh and Awartani (2014)	Analysis of bank distress in the Gulf Cooperation Council countries.	Good management lowers the likelihood of distress. Competition and diversification bad for the health of banks. CAMEL variables and macroeconomic indicator important in the identification of distressed banks.

3.2 Bank Distress During the Global Financial Crisis

What is bank distress and in what forms does it manifest? In broad terms, bank distress is a condition in which a bank's realized or expected income from existing assets deteriorates to the extent that it impairs the bank's current or future ability to honor commitments to its creditors. More specifically, following the nomenclature of Demirguc-Kunt (1989), a bank is defined to be economically insolvent when the present value of its assets, net of implicit and explicit external guarantees, falls below the present value of claims from the banks' creditors.

A bank whose asset value deteriorates sufficiently close or below the value of non-equity claims faces a set of possible resolutions, a precise realization of which depends on the size and systemic importance of the bank as well as on the regulatory infrastructure, in particular the bank resolution mechanisms, deposit insurance arrangements, and the allocation of bank supervisory authority. For a more detailed discussion of failed bank resolution options see DeYoung et al. (2013) and Santomero and Hoffman (1996). At one end of the spectrum, a distressed bank may be closed and its assets liquidated. Alternatively, it may be allowed to continue its operation with explicit government support in the form of asset- or liability-oriented measures.

For the purposes of this paper, we categorize different types of manifestation of bank distress into two broad groups, namely:

- **Bank closure**, which includes all types of resolution in which the charter of the insolvent institution is revoked, or subsumed by a non-distressed acquiring institution. As such, we consider as bank closures the set of the following events: liquidations, court bankruptcies, regulatory receiverships, and distressed mergers. Distressed mergers are defined as mergers, in which the merged entity's regulatory Tier 1 capital ratio falls below the Basel II threshold of 6% for at least two years prior to the merger.

- **Open-bank resolution**, defined as the resolution in which the independent charter of the distressed bank is preserved, and the institution continues to operate as the independent entity. Open-bank resolutions typically consist of a government bailout (e.g. investment in bank capital), coupled with a set of measures to improve the long-term viability of the bank (e.g. reallocation of the toxic assets to a bad bank).

In what follows, we explain the construction of our cross-country database on distressed bank resolutions during the recent financial crisis in the U.S. and Europe. We also report a selection of summary statistics on distressed bank resolution in our sample, which gives a top-down perspective on the type and size of resolutions across different countries.

For a more complete discussion and for the exposition of main developments during the recent banking crisis in the U.S. and Europe, an interested reader may refer to Stolz and Wedow (2010). A more general discussion of failed bank resolution options and of their respective costs and benefits can be found in DeYoung et al. (2013) and Santomero and Hoffman (1996).

3.2.1 Construction of the Database on Distressed Bank Resolutions During the 2007-12 Crisis in the U.S. and Europe

This paper features a comprehensive database of distressed bank resolutions during the recent financial crisis in the U.S. and Europe. To construct the database, we collect information from several publicly available sources. First, we use the bank status indicators in the *Bankscope* and the *SNL Financial* databases to construct a list of bank closures during the period 2007-12. The status indicators distinguish between several different types of bank exit, including bankruptcy, liquidation, dissolution of bank charter, and the exit via acquisition by another bank. In most of the cases, *Bankscope* and *SNL* provide a date of the exit. For the subset of cases in which the precise date is not available, we obtain the date by examining the public news sources in *Factiva* and *LexisNexis*.

In order to obtain a comprehensive list of bank closures in the U.S. we supplement the bank status information from Bankscope and SNL by the publicly available Failed Bank list compiled by the FDIC, the U.S. deposit insurance fund. The list includes the set of U.S.-chartered commercial banks that were closed by the FDIC, which acts as a receiver for the failed banks. In this capacity, FDIC is responsible for a disposal of failed bank assets and the distribution of proceeds to the creditors[4]. Most failed banks acquired by the FDIC are sold to other banks via the so-called "purchase-and-assumption" transactions, in which the buyer of the failed bank's assets also acquires its deposits. Since the acquisition of new depositors implies a positive charter value for the acquiring banks (e.g. via the possibility of new lending relationships, or generation of fees), buyers of failed banks are typically willing to bid a premium to acquire the failed bank. In Europe, there is unfortunately no other centralized source (not even at the national level) of regulatory closures on-par with the FDIC's failed bank list, so all our bank closure information there comes from *Bankscope* and the *SNL Financial*.

Next, moving to open-bank resolutions, most of our data on open-bank resolutions in the U.S. consist of the bank equity infusions under the Capital Assistance Program (CAP) of The Troubled Asset Relief Program (TARP). The participating bank names and the corresponding TARP equity issuance dates are obtained from publicly available regulatory sources.

In Europe, the open-bank resolution information is obtained from several sources. For the countries that are part of the EU (most of our sample), we consult the publicly available database of State Aid cases at the European Commission website. The State Aid request must be submitted by any EU-member government that considers an intervention within the domestic economy that may distort a competitive environment at the EU level. While not specific to the banking sector, the State Aid procedures in

[4]In most cases, proceeds generated by the failed bank asset sale fall below the total value of deposits, making the FDIC the residual claimant in the process.

practice cover most of the national bail-out programs for banks in the EU countries. European Commission typically conditions the approval of the aid requests on the restructuring of the intervened banks, often laying-out specific requests on the restructuring measures, which made the EU State Aid framework the de-facto failed bank resolution mechanism in the EU during the recent banking crisis. In order to make it consistent with the TARP events in the U.S., the European list of open-bank resolutions is limited to the government recapitalizations. We exclude other types of interventions such as state guarantees on bank liabilities, whose aim was primarily to prevent bank runs (and was typically applied to all major banks in the country), rather than being specifically targeted at the insolvent institutions (see Laeven and Valencia, 2008). For countries, that are not the part of the EU, we obtain the list of bank recapitalizations by manually searching publicly available news sources in *Factiva* and *LexisNexis*.

Table 3.2 provides a top-down view of the bank distress database. Several interesting observations emerge from the table. First, bank distress has been pervasive during the crisis: in the countries under study, the assets attributed to banks in distress represented on average about 30% of the total commercial banking assets[5], ranging from 5% in Luxembourg to 87% in Greece. Second, banks resolved via closure tend to be smaller on an individual as well as on aggregate basis, compared to banks resolved via open-bank assistance. The average size of a closed bank in Europe (the U.S.) is about 39 billion USD (7 billion USD), whereas the average size of a bank resolved via open-bank assistance is 190 billion USD in Europe and 45 billion USD in the U.S. In aggregate terms, bank closures represent about 15% (30%) of distressed bank assets in Europe (respectively, the U.S.). A further disaggregation of the latter result in Europe reveals a substantial cross-country variation in the occurrence of bank closures relative to open-bank assistance in resolution of banks in distress.

[5]Aggregated commercial banking assets are measured at the outset of the financial crisis in 2008.

Table 3.2 – Bank Distress Events

Country	Bank Distress Events (period 2007-12)								Size of Bank Sector in 2008
	Number of Distressed Banks				Book Assets of Distressed Banks (in Billion USD)				
	Open Bank Assist.	Bank Closure: Outright	Bank Closure: Distr. Merger	Total	Open Bank Assist.	Bank Closure: Outright	Bank Closure: Distr. Merger	Total	
Austria	5	0	1	6	597	0	7	604	2147
Belgium	1	1	1	3	847	4	12	864	3673
Denmark	43	1	1	45	744	2	6	753	1657
France	8	0	1	9	6792	0	663	7455	21728
Germany	7	2	14	23	4112	2	642	4755	12173
Greece	9	0	2	11	496	0	30	526	602
Iceland	5	2	0	7	140	6	0	146	172
Ireland	5	1	1	7	430	12	24	465	1595
Italy	14	11	37	62	320	8	1615	1943	5562
Luxembourg	2	2	0	4	42	13	0	55	1263
Netherlands	8	1	0	9	2355	1	0	2356	7108
Portugal	8	0	3	11	431	0	9	439	704
Spain	8	0	23	31	1071	0	891	1963	5860
Sweden	1	0	1	2	227	0	29	255	1830
United Kingdom	18	7	7	32	8237	28	753	9019	23271
Europe	142	28	92	262	26841	76	4680	31597	89344
USA	275	532	134	941	12341	3602	1132	17075	36235

Notes:

[a] Banks are defined as distressed when they: 1. cease to exist as a going concern (‘Closure’), 2. receive an assistance from the domestic authority (‘Assistance’), or 3. undergo a distressed merger (‘Distr. Merger’). In the U.S., bank closures are identified from the FDIC failed bank list (http://www.fdic.gov/bank/individual/failed/banklist.html). In Europe closed banks are identified as the institutions whose Bankscope ‘Status‘ indicator equals ‘Dissolved’, ‘Liquidation’, or ‘Bankruptcy’. Distressed mergers are defined as mergers, in which the merged entity’s Tier 1 capital ratio (scaled by the risk-weighted assets) falls below the Basel II threshold of 6% for two years prior to the merger. Bank assistance transactions consist of re-capitalizations, bridge loans, and asset purchases by the relevant domestic authority. For European banks we collect the assistance transactions from the European Commission State Aid Cases (http://ec.europa.eu/competition/state_aid/register/). In the U.S., assistance transactions are identified from the FDIC failed bank list.

[b] Some banks experience multiple distress events in a sequence. In such cases, the table reports only the first event in the sequence. Panel A shows the distribution of distressed banks across countries and years. Panel B reports the number of distress events by the type of event, as well as the total amount of assets held by distressed banks (measured as the total book assets at the fiscal year end of 2008). The last column in Panel B is the sum of book assets across all bank within a particular country, at the end of 2008. In computing the total assets of the sector we only take into account the numbers from the consolidated financial statements. If the consolidated statement for a given bank is unavailable we use its unconsolidated report instead. The book value of bank assets is taken from Bankscope.

3.2.2 Sample

The sample covers banks from the U.S. and the following 15 countries from the Western Europe: Austria, Belgium, Denmark, France, Italy, Iceland, Ireland, Germany, Greece, Luxembourg, Netherlands, Portugal, Spain, Sweden, and United Kingdom. We follow the banks from 2005 until one of the following three types of exits, defined above: (1) bank closure, (2) open-bank assistance, and (3) other censoring events, such as non-distressed mergers or the end of the sample period in December 2012.

Bank balance sheet data are obtained from Bankscope. We limit our analysis to the following types of banks (bank types defined by Bankscope): (1) bank holding companies, (2) commercial banks, (3) cooperative banks, (4) mortgage banks, and (5) savings banks. When a given bank reports accounts at different levels of consolidation, we only keep the reported figures at the highest level of consolidation[6]. Unless otherwise stated, all accounting measures are scaled by the total book value of assets in the same fiscal period. Most of the banks in our sample are private.

Each record in our distress resolution database is manually linked to the bank-level accounting information in *Bankscope*, based on the institution name, and location. We manage to match most of the records in the database of distress events to the corresponding bank records in *Bankscope*. If an institution experiences multiple events in a sequence (for example, several government recapitalizations in succession) the subsequent analyses only considers the first event in the sequence and discards the rest (i.e. this is equivalent to assuming that the bank exited the sample after the first distress event). This is done in order to avoid double counting such institutions as distressed, and thus inflating the significance of any potential differences between the distressed and non-distressed groups of banks.

[6]In practice, keeping only the data at the highest available level of consolidation implies keeping the observations with Bankscope consolidation codes equal to C1, C2, or U1.

Table 3.3 – Sample Summary

	Count	Mean	S.D.	P1	P25	P50	P75	P99
Capital								
Equity / Total Assets	74177	0.103	0.086	0.023	0.074	0.091	0.112	0.532
Regulatory Tier 1 Capital Ratio	57039	0.151	0.169	0.048	0.106	0.127	0.161	0.472
Regulatory Tier 2 Capital Ratio	56622	0.014	0.015	0.000	0.010	0.012	0.013	0.073
Risk-Weighted Assets / Total Book Assets	51067	0.711	1.450	0.274	0.624	0.717	0.798	1.010
Asset Quality								
Unreserved Impaired Loans / Equity	56525	0.115	0.493	-0.164	-0.048	0.005	0.135	1.894
Loan Loss Provisions / Gross Loans	72076	0.010	0.437	-0.012	0.000	0.004	0.009	0.064
Management								
Non-Interest Expense/ Gross Revenues	73323	0.698	0.335	0.195	0.588	0.673	0.763	1.648
Total Non-Interest Expenses / Total Assets	71688	0.007	0.017	0.000	0.002	0.005	0.010	0.032
Earnings								
Return On Avg Assets (ROA)	74107	0.006	0.032	-0.044	0.002	0.006	0.011	0.039
Return On Avg Equity (ROE)	74091	0.053	0.229	-0.616	0.028	0.064	0.113	0.327
Net Interest Margin / Total Assets	73556	0.012	0.026	0.000	0.003	0.008	0.019	0.046
Interest Expense / Interest-Bearing Liab.	71688	0.023	0.059	0.003	0.014	0.021	0.028	0.052
Liquidity								
Net Loans / Tot Dep and Bor	71390	0.723	0.208	0.099	0.623	0.744	0.848	1.071
Liquid Assets / Dep and ST Funding	73515	0.149	0.282	0.011	0.048	0.092	0.166	0.948
Size								
Logarithm of Total Book Assets	74180	6.392	1.502	4.635	5.293	6.052	7.017	11.790
Total Book Assets (in million USD)	74180	7534	73129	103	199	425	1115	131910

Notes:
[a] The table shows summary statistics for a sample of European and U.S. banks with book assets in excess of USD100 million during the period 2005-12. Unless otherwise mentioned, all variables are scaled by the total book value of assets.

Table 3.3 reports summary statistics for a selection of accounting fundamentals that we study in the subsequent analysis. Our choice of the accounting ratios follows the existing literature and tries to capture the most representative accounting fundamentals from 5 dimensions of the CAMEL assessment framework[7], which is a supervisory rating system developed by the U.S. bank regulators in the early 1980s[8]. The accounting fundamentals studied in the subsequent analysis are the following:

1. *Capital adequacy*: book equity (% of total book assets), regulatory Tier 1 ratio (% of total book assets), regulatory Tier 2 ratio (% of total book assets),

2. *Asset quality*: risk-weighted assets (% of total book assets), unreserved impaired loans (% of book equity), loan loss provisions (% of gross loans),

3. *Management quality*: non-interest expense (% of gross revenues), total non-interest expenses (% of total assets),

4. *Earnings quality*: return on average assets (ROA), return on average equity (ROE), net-interest margin (% of total assets), interest expense (% of interest-earning liabilities),

5. *Liquidity*: net loans (% of non-equity funding), and liquid assets (% of deposits and short-term funding).

Each of the above variables is winsorized at the 1% level at each tail to avoid the influence of the outliers. In order to avoid sample attrition due to missingness of the individual covariates in the subsequent multivariate regressions and prediction exercises, we impute the missing values of each variable by setting them to their respective unconditional (winsorized) sample means.

Table 3.4 breaks the total variation in each accounting measure to within-bank, within-country, and between country variation. In most of the subsequent analysis, we control for the country-year interactions (explained in the next section), thus essentially exploiting the within-country variation to identify the coefficients.

[7] In selecting the subset of CAMEL variables, we test about 500 accounting ratios contained in *Bankscope* database. Our final choice of variables considers the level of missing values, and the fraction of variation captured by a variable within each CAMEL group.

[8] The name of the system is an acronym that relates to the dimensions of bank conditions assessed by the system, namely: Capital adequacy, Asset quality, Management quality, Earnings, Liquidity, and Sensitivity to market risk.

Table 3.4 – Decomposition of Variation in Accounting Fundamentals

Variable	Fraction of the Total Sum of Squared Errors: Within Firm	Within Country	Between Country
Capitalization			
Equity / Total Assets	0.23	0.75	0.02
Regulatory Tier 1 Capital Ratio	0.25	0.71	0.04
Regulatory Tier 2 Capital Ratio	0.57	0.40	0.03
Risk-Weighted Assets / Total Book Assets	0.20	0.77	0.03
Asset Quality			
Loan Loss Res / Gross Loans	0.39	0.55	0.07
Unreserved Impaired Loans/ Equity	0.53	0.44	0.03
Management			
Non-Interest Expense/ Gross Revenues	0.34	0.64	0.02
Total Non-Interest Expenses / Total Assets	0.23	0.74	0.04
Earnings			
Return On Avg Assets (ROA)	0.26	0.55	0.19
Return On Avg Equity (ROE)	0.45	0.54	0.01
Net Interest Margin / Total Assets	0.48	0.47	0.05
Interest Expense/ Interest Bearing Liab.	0.61	0.35	0.04
Liquidity			
Net Loans / Tot Dep and Bor	0.25	0.56	0.19
Liquid Assets / Dep & ST Funding	0.24	0.53	0.23

Notes:

[a] The sample consists of the Western European and the U.S. banks covered by Bankscope. For each bank we use the accounting information from its consolidated statements (Bankscope codes C1 or C2), or from the unconsolidated statements, if the consolidated statements are unavailable (Bankscope code U1). The time period of the analysis is January 2005 - December 2012.

[b] Let C, I, and T denote total number of countries, firms and time units (years) in the sample. We measure the total variation in variable x as $\sum_{c,i,t}(x_{c,i,t}-\bar{\bar{\bar{x}}})^2$, where c, i, and t are indexes for countries, firms, and time, respectively, and $\bar{\bar{\bar{x}}} = \frac{1}{I*T}\sum_{i,t} x_{c,i,t}$. It can be shown that the total variation is a sum of within-firm variation ($\sum_t(x_{c,i,t} - \bar{x}_{c,i})^2$), within-country variation ($\sum_i(\bar{x}_{c,i} - \bar{\bar{x}}_c)^2$) and between-country variation ($\sum_c(\bar{\bar{x}}_c - \bar{\bar{\bar{x}}})^2$). The tables reports each of the three components as a fraction of the total variation.

3.3 Explaining Within-Country Variation in Bank Distress by Accounting Fundamentals

We begin by analyzing the extent to which bank closures and open-bank resolutions are explainable by bank accounting fundamentals. In this section, we only focus at modelling the within-country variation in bank distress and control for the unobservable country-year trends by including a set of country-year dummies[9]. Section 3.3.1 analyzes the univariate dynamics of a set of accounting covariates prior to the onset of bank distress, with the aim of identifying the covariates that best discriminate between distressed and non-distressed banks prior to the actual distress

[9]Country-year trends are likely to influence the probability of bank distress directly as well as via the bank accounting fundamentals. The consistent estimation of coefficients on accounting fundamentals thus necessitates inclusion of county-year fixed effects.

events. Section 3.3.2 presents the estimation results of the multivariate bank failure models.

3.3.1 Time Path of Bank Performance Indicators Prior to Distress Event

It is instructive to begin by analyzing bank solvency from developments in a selection of bank indicators in the periods leading up to a distress event. The main aim of this analysis is to identify the performance dimensions in which distressed banks diverge from their non-distressed peers and shed light on the possible drivers (or at least symptoms) of bank distress. The subsequent analysis in this section distinguishes between closed- and open-bank distress resolutions, thus trying to capture any potential heterogeneity in the drivers of the two manifestations of bank distress. In order to avoid results being driven by a relatively large number of distress events in the U.S. (see Table 3.2), we split the estimation sample to subsamples of the U.S. and Western European banks.

We approach the identification of the relative performance of distressed to non-distressed banks in the periods leading up to distress by estimating a series of specifications of the following form:

$$y_{ict} = \alpha_{ct} + \sum_{j=0}^{n} \phi_j f_{ict}^{j} + \epsilon_{ict}, \tag{3.1}$$

where y is a bank-specific performance measure of interest, f_{ict}^{j} is an indicator of bank i becoming distressed within $[j, j+1)$ year from time t, and i, c, t denote firm, country, and time indices, respectively. We control for country-year specific trends and invariant characteristics by including country-year fixed effects, α_{ct}. The model is estimated separately for bank closures (closure by the regulator, bankruptcy, liquidation, distressed dissolution, distressed merger) and for open-bank resolutions (consisting primarily of government recapitalizations), as well as for the U.S.[10] and Western Europe.

Within this context, we trace the evolution of CAMEL bank performance measures, y_{ict}, described in Section 3.2.2 (see Table 3.3). Each of the accounting variables is standardized to have a zero mean and variance of one, implying the following interpretation of a coefficient ϕ_j: banks experiencing distress event between j and

[10]Model 3.1 in the U.S. is estimated only with year-fixed effects.

$j+1$ years in the future display on average ϕ_j standard deviations higher or lower value of y than their non-distressed peers, controlling for country-year specific trends.

Panels A and B of Figure 3.1 present the results from the estimation of equation 3.1, for European and the U.S. samples[11], respectively. The figure plots the estimates of coefficients ϕ_j for each bank performance measure listed above.

The most important result pertains to bank capitalization: distressed banks in both Europe and the U.S. tend to be significantly under-capitalized with respect to their non-distressed peers. The economic magnitude of the result is particularly sizable for bank closures, with the distressed/non-distressed Tier 1 capital lag reaching 0.4 standard deviations in a year before the distress event. In Europe, the relative Tier 1 under-capitalization of distressed banks spans the period of at least 5 years before the distress event, while in the U.S. the under-performance is particularly notable during the three years before the event. Finally, U.S. distressed banks undergoing an open-bank resolutions are on average significantly better capitalized than their European counterparts in the same distress group.

While undercapitalized along the Tier 1 capital metric, distressed banks, perhaps surprisingly, exhibit higher levels of Tier 2 capital than their non-distressed counterparts. This pattern is particularly distinguishable in the U.S., whereas in Europe it applies only to bank closures. The positive relation between Tier 2 capital and bank risk suggests that Tier 2 capital should not be considered as a gauge of bank health and resilience, at least not in the same manner as Tier 1 capital. If anything, high levels of Tier 2 capital (i.e. relative to other banks) are indicative of high bank risk. Unfortunately, sparsity of Bankscope coverage of regulatory capital components prevents us from exploring the source of the disparity in more detail. One plausible explanation for the observed pattern is that banks that eventually become distressed engage in relatively risky lending and account for this risk by increasing the amount of general loan loss provisions and loan loss reserves, both of which under some conditions count as Tier 2 capital.

Decline in Tier 1 capitalization of distressed banks coincides with deterioration in their profitability, particularly for the group of banks that are eventually closed. Deterioration in profitability, in turn, is related to increasing loan-loss provisions and impairment charges, as well as to declining interest margins and operating efficiency (measured by the fraction of non-interest expenses in bank gross revenues). A notable exception to the above pattern are the U.S. banks involved in open-bank resolution; for this group, profitability, asset impairments, and operating efficiency are on par

[11] In the case of the U.S., the country-year fixed effects are substituted with year-fixed effects.

with the non-distressed banks, suggesting that apart from being undercapitalized these banks were relatively healthy in terms of their quality of earnings and assets.

In terms of their funding, distressed banks of both types tend to rely on less stable sources of funding and pay on average a higher price for funding then their non-distressed peers. This pattern is especially pronounced for banks that are subsequently closed.

Finally, a comparison of pre-event trends in accounting fundamentals between banks in Europe and the U.S. reveals a strong deterioration in fundamentals for bank closures in the U.S., whereas no such clear time-pattern is present in Europe. A temporal deterioration in fundamentals of the closed banks in the U.S. is particularly pronounced in the case of Tier 1 capital, unreserved impaired loans, loan loss provisions, non-interest expenses, and profitability.

3.3.2 Multivariate Prediction of Bank Distress

After analyzing the univariate divergences between distressed and non-distressed banks for select performance metrics, we now turn to modelling bank distress within a multivariate setting. Specifically, we model the probability of a bank becoming distressed within one year from the publishing of its accounting information as a function of the accounting performance measures analyzed in the previous section[12]. To this end, we estimate the following specification:

$$Pr(\text{Distressed}_{ict} = 1) = \text{Logit}(\alpha_{ct} + x'_{ict}\theta + \epsilon_{ict}), \tag{3.2}$$

where D_{ict} is the indicator of a bank becoming distressed within 1 year from time t, and i, c, and t denote firm, country, and time indices, respectively. As before, we present results separately for the two types of distress, as well as for Europe and the U.S. Estimation of specification in Equation 3.2 is equivalent to the estimation of an exponential hazard model, in which a firms' probability of distress does not depend on its age.

The estimation results are reported in Table 3.5. As in the previous section, all explanatory variables are standardized to have a mean zero and a unit variance, so that the magnitude of the reported coefficient corresponds to the impact of one standard deviation increase in the explanatory variable on the log-odds ratio.

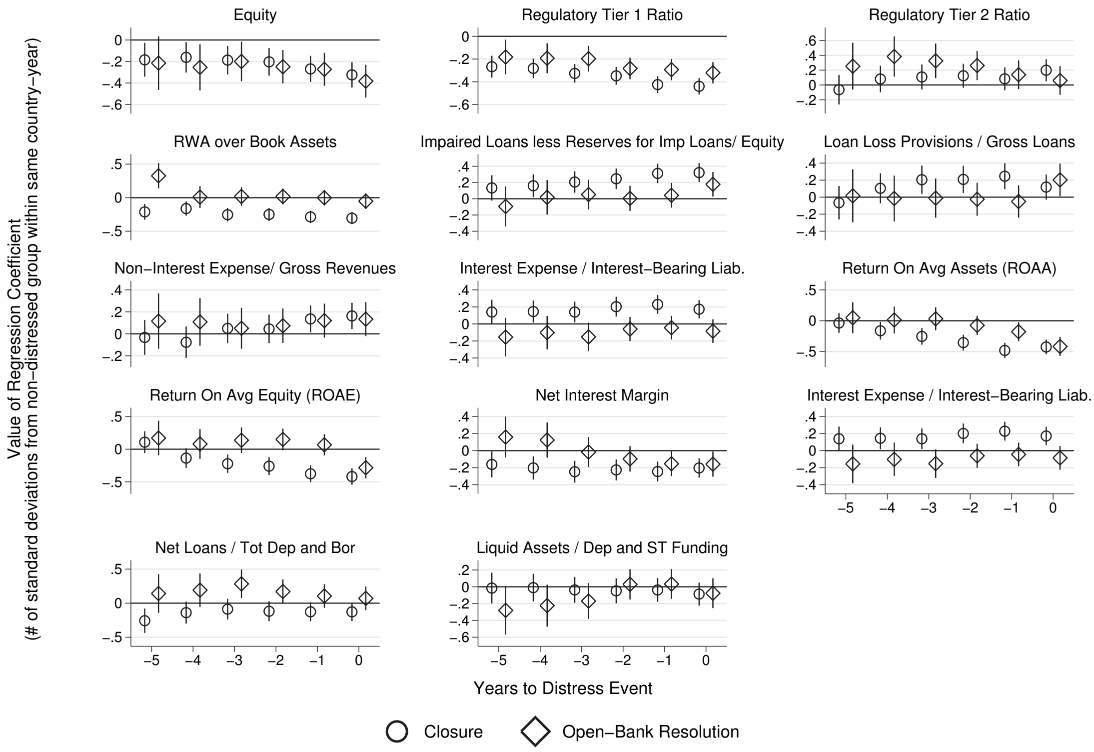
[12]Accounting measures within some CAMEL dimensions, e.g. earnings quality, are highly correlated. In order to avoid multicollinearity, the multivariate analysis below only includes one of the highly correlated pair in the same CAMEL category.

Consequently, the absolute magnitude of the coefficient can be used to judge the relative economic importance of different variables in the specification.

The overall outcome of the regression analysis reveals that the likelihood of bank closure increases with (1) the degree of Tier 1 undercapitalization, (2) asset risk (measured by the ratio of RWA to book assets), (3) the amount of unreserved loan loss impairments, (4) cost of funding, and (5) the degree of operational inefficiency, (6) a decrease in bank profitability, measured by the interest margin, and (7) a decrease in asset liquidity, though the effect of the latter is statistically insignificant.

The relation between bank closure and Tier 2 capitalization is positive in Europe and negative in the U.S. (both highly statistically significant). The opposite sign may be explained by the fact that the composition of regulatory capital strongly depends on the regulatory requirements and enforcement within the specific country. The World Bank survey of bank regulators conducted in 2011 reveals substantial cross-country variation in the instruments that count as capital. To the extent that these instruments differ in their capacity to absorb losses, their implication for predicting bank closure is obviously country-dependent. Therefore, it is important to explore the regulatory consequences for predicting bank distress across countries, which we do in the next section.

In terms of its explanatory power, the bank closure model explains bank closures with substantially higher degree of accuracy in the U.S. (with pseudo R-squared of 40%) than in Europe (13%). In the light of the univariate dynamics reported in Figure 3.1 this is not surprising, because most accounting ratios reported by the distressed banks in the U.S. exhibit clear negative trends already several years prior to the distress event. If we change the forecasting horizon in the U.S. to two years in the future, the R-squared of the model drops to around 20%. A possible reasons why explanatory power of the U.S. bank closure prediction model increases so abruptly for a 1-year forecasting horizon (with respect to the 1-2 year horizon) is that the banks in the U.S. may be subject to a so-called “controlled-failure” process, whereby the regulator (FDIC) identifies the distressed bank some time prior the observed failure, and forces it to clean the balance sheets before the bank is officially dissolved.

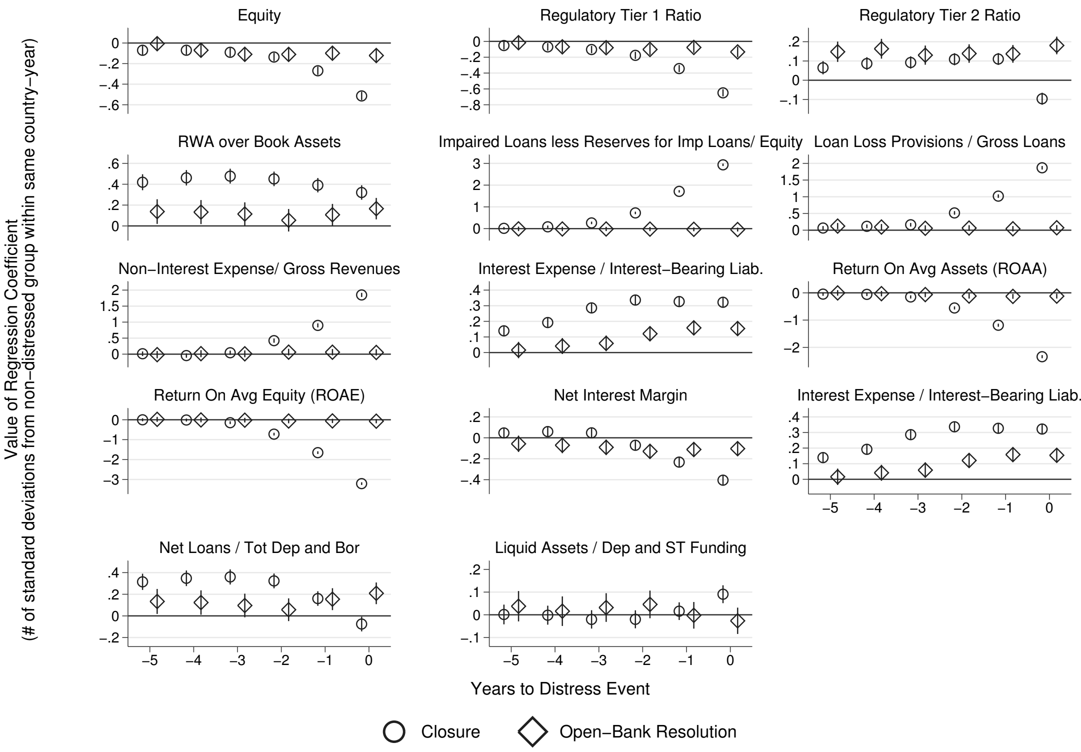


(a) Europe

Figure 3.1 – Relative performance of distressed banks along select accounting ratios in years prior to the distress event. The figure plots the estimated coefficients together with corresponding confidence intervals from the following specification:

$$y_{ict} = \alpha_{ic} + \textstyle\sum_{j=0}^{5} \phi_j f_{ict}^j + \epsilon_{ict},$$

where $f_{ict}^j = 1_{\text{Bank i becomes distressed within [j,j+1) year from time t}}$, and i, c, t denote firm, country, and time indices, respectively. α_{ic} denotes country-year fixed effects. The model is estimated separately for bank closures (closure by the regulator, bankruptcy, liquidation, distressed dissolution, distressed merger) and for open-bank resolutions (government recapitalizations). Panel A (resp. B) shows the estimated coefficients together with the 95% confidence intervals for the models estimated in the EU (resp. U.S.). Standard errors are clustered at the firm level. Each of the y variables is standardized to have a zero mean and variance of one, implying the following interpretation of a coefficient ϕ_j: banks experiencing distressed event between j and $j+1$ years in the future display on average ϕ_j standard deviations higher/lower value of y than their non-distressed peers, controlling for country-year specific trends.



(b) United States

Figure 3.1 – Continued from previous page.

Table 3.5 – Modelling of European and the U.S. Bank Distress

	Dependent variable is distress within 1 year					
	Bank Closure			Open-Bank Resolution		
	(1) EU	(2) US	(3) Combined	(4) EU	(5) US	(6) Combined
Regulatory Tier 1 Ratio	-2.20***	-3.17***	-3.21***	-0.72**	0.16	0.07
	[0.35]	[0.22]	[0.18]	[0.28]	[0.10]	[0.10]
Regulatory Tier 2 Ratio	0.32***	-0.30***	-0.01	-0.13	0.13	-0.02
	[0.09]	[0.12]	[0.08]	[0.12]	[0.14]	[0.09]
RWA over Book Assets	0.03	0.51***	0.37***	0.37***	-0.18*	0.03
	[0.12]	[0.10]	[0.07]	[0.12]	[0.10]	[0.07]
Unreserved Impaired Loans/ Equity	0.19**	0.22***	0.20***	0.09	-0.14*	-0.05
	[0.09]	[0.03]	[0.03]	[0.09]	[0.08]	[0.06]
Loan Loss Provisions / Gross Loans	0.01	0.32***	0.28***	0.27***	0.12*	0.15***
	[0.10]	[0.04]	[0.03]	[0.06]	[0.07]	[0.05]
Interest Expense / Interest-Bearing Liab.	0.25*	1.10***	0.72***	0.01	-0.24	-0.10
	[0.14]	[0.09]	[0.06]	[0.12]	[0.18]	[0.10]
Net Interest Margin	-0.39	-0.17	-0.33***	0.07	-0.16	-0.04
	[0.28]	[0.11]	[0.11]	[0.15]	[0.12]	[0.09]
Non-Interest Expense/ Gross Revenues	0.10	0.11***	0.15***	0.10	0.15***	0.12***
	[0.11]	[0.03]	[0.03]	[0.09]	[0.05]	[0.04]
Liquid Assets / Dep and ST Funding	0.07	0.02	0.14*	-0.05	-0.39***	-0.19**
	[0.12]	[0.12]	[0.08]	[0.11]	[0.15]	[0.09]
Net Loans / Tot Dep and Bor	-0.00	-0.00	0.06	0.18	0.47***	0.29***
	[0.13]	[0.11]	[0.08]	[0.13]	[0.11]	[0.08]
Log(Assets)	0.06	0.08*	0.07**	0.46***	0.49***	0.49***
	[0.06]	[0.04]	[0.03]	[0.06]	[0.04]	[0.03]
No. Events	112	533	645	137	273	410
No. Obs.	14786	46930	61716	8664	33110	41774
Pseudo R2	0.128	0.406	0.348	0.149	0.095	0.097
Effects	Country * Year	Year	Country * Year	Country * Year	Year	Country * Year

Notes:

[a] The table reports the estimation coefficients from the following specification:

$$P(D_{ict} = 1) = \text{Logit}(\alpha_{ic} + x'_{ict}\theta_t + \epsilon_{ict}) \quad (3.3)$$

where D_{ict} is the indicator of a bank becoming distressed within 1 year from time t, and i, c, and t denote firm, country, and time indices, respectively.

[b] Each column corresponds to the vintage of the accounting information that is used to model the bank distress events. In Europe, distress events are defined as the first time a given bank in a sample experiences one of the following: (a) bankruptcy/liquidation, (b) equity injection by the st ate (including nationalization), or (c) bridge loan by the state. For the U.S. banks, the distress indicator is constructed from the FDIC Failed Bank List (`http://www.fdic.gov/bank/individual/failed/banklist.html`). To avoid sample attrition due to missingness of the individual covariates, we impute the missing values of each variable in the specification by setting them to their respective sample means. All explanatory variables are next standardized to have a mean of zero and standard deviation of one. Bootstrapped standard errors are reported in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Moving next to the results for open-bank resolutions, we note that the correlations between the likelihood of the event and covariates display similar directional patterns as in the case of bank closures, even though with varying degrees of statistical and economic significance.

In contrast to bank closures, bank size is statistically and economically more significant in the case of open-bank resolutions (the size coefficient being more strongly positive), which is consistent with the too-big-to-fail proposition, asserting that a failure of large institutions engenders disproportionately larger costs for the economy, prompting regulators and governments to resolve these institutions on a going concern basis.

In terms of the economic magnitude, particularly important determinants of open-bank distress resolution are the riskiness and liquidity of bank assets. Banks experiencing state or regulatory intervention tend to have more risky and less liquid assets than their surviving counterparts.

Comparison of the direction and magnitude of coefficients across all models suggests a high degree of overlap between the bank closure models in the U.S. and Europe and the open-bank assistance model in Europe. On the other hand, accounting fundamentals perform relatively poorly in explaining open-bank assistance events (i.e. TARP) in the U.S., suggesting that these events were driven by other non-fundamental drivers. This is in line with Bayazitova and Shivdasani (2012), who show that capital infusions under TARP were driven by strategic considerations, such as certification effects, and the constraints that TARP funds imposed on banks' compensation schemes.

3.4 Further Analysis on the Information Content of Accounting Fundamentals

The previous section demonstrated that the accounting fundamentals explain a significant proportion of within-country variation in the incidence of bank distress. This section examines the information content of the accounting fundamentals by studying the ability of bank accounting numbers (1) to identify distressed banks within individual countries (Section 3.4.1), and (2) to explain the country-level incidence of bank distress during 2007-10 (Section 3.4.2).

3.4.1 How informative is bank accounting disclosure in identifying distressed banks within countries?

In this section we evaluate the informativeness of the bank failure models developed in Section 3.3.2 in discriminating between distressed and non-distressed banks within each country in our sample. The informativeness of a model is measured by the area under the Receiver operating characteristic (ROC) curve[13] (AUC) from a classification exercise in which the model-implied predictions are used to predict bank distress within a specific country. A particularly useful interpretation of the AUC is that it is the probability that the randomly chosen distressed bank observations exhibit higher values of the predicted model score than the randomly chosen surviving observation. At one end of the spectrum, a completely uninformative classifier has the AUC of 0.5, whereas a perfectly predictive classifier has an ROC of 1[14].

We assess the within-country predictive performance of different model predictions, by computing AUCs for each individual country. AUCs are obtained from the non-parametric ROC estimation, using bootstrap.

Panels A, B, and C of Table 3.6 report the ROC results for predicting bank closure, open-bank assistance, and generally defined bank distress events (either closure or assistance), respectively. Each column corresponds to the AUCs pertaining to the particular model. For each country/predictor we report the estimated AUC and its standard error. The table includes the results only for countries with more than six events of a particular type[15]

[13]Receiver Operating Characteristic (ROC) curve summarizes the performance of a continuous predictor in predicting a binary outcome by plotting the false-positive rates against the true-positive rates for varying models score threshold levels.

[14]This assumes that a classifier is positively associated with bank distress, i.e. higher values of the classifier signal a higher likelihood of a distress event.

[15]The variability of AUC estimates for countries with lower number of events makes the resulting estimates less meaningful.

Table 3.6 – Informativeness of Accounting-Based Bank Distress Prediction Models: Areas Under ROC Curve[d] Across Countries

Model type:		Logistic Regression Model[b] (all countries)								
Dependent variable:		Open-Bank Assist.			Bank Closure			Bank Distress		
Estimation sample:	# Events[c]	All	EU	U.S.	All	EU	U.S.	All	EU	U.S.
Panel A: Use model score to predict **bank closure events** in...										
ALL	786	0.617	0.826	0.361	0.937	0.926	0.935	0.928	0.912	0.927
		[0.027]	[0.029]	[0.040]	[0.014]	[0.015]	[0.014]	[0.016]	[0.018]	[0.016]
DEU	16	0.426	0.500	0.376	0.932	0.918	0.908	0.890	0.865	0.779
		[0.067]	[0.068]	[0.064]	[0.014]	[0.027]	[0.025]	[0.023]	[0.051]	[0.073]
ESP	23	0.783	0.799	0.737	0.922	0.942	0.898	0.901	0.906	0.889
		[0.030]	[0.034]	[0.027]	[0.010]	[0.012]	[0.011]	[0.014]	[0.018]	[0.011]
GBR	14	0.647	0.623	0.665	0.698	0.697	0.679	0.680	0.627	0.690
		[0.078]	[0.074]	[0.080]	[0.076]	[0.086]	[0.069]	[0.076]	[0.091]	[0.073]
ITA	48	0.667	0.724	0.612	0.849	0.841	0.839	0.839	0.825	0.836
		[0.057]	[0.040]	[0.067]	[0.026]	[0.028]	[0.026]	[0.026]	[0.029]	[0.028]
USA	665	0.637	0.855	0.321	0.954	0.949	0.953	0.945	0.934	0.945
		[0.019]	[0.025]	[0.048]	[0.012]	[0.014]	[0.013]	[0.014]	[0.015]	[0.015]
Panel B: Use model score to predict **open-bank assistance events** in...										
ALL	417	0.838	0.819	0.833	0.709	0.675	0.705	0.763	0.762	0.762
		[0.031]	[0.018]	[0.062]	[0.052]	[0.050]	[0.056]	[0.042]	[0.034]	[0.056]
DEU	7	0.785	0.791	0.773	0.782	0.680	0.793	0.789	0.750	0.798
		[0.254]	[0.255]	[0.250]	[0.253]	[0.242]	[0.255]	[0.254]	[0.248]	[0.256]
DNK	43	0.655	0.708	0.600	0.537	0.526	0.517	0.598	0.621	0.557
		[0.028]	[0.018]	[0.038]	[0.109]	[0.102]	[0.118]	[0.078]	[0.047]	[0.098]
ESP	8	0.739	0.873	0.524	0.799	0.818	0.809	0.876	0.886	0.871
		[0.069]	[0.075]	[0.120]	[0.187]	[0.165]	[0.178]	[0.119]	[0.100]	[0.118]
FRA	8	0.833	0.837	0.729	0.776	0.787	0.783	0.812	0.836	0.799
		[0.015]	[0.008]	[0.076]	[0.015]	[0.039]	[0.019]	[0.012]	[0.014]	[0.011]
GBR	18	0.818	0.802	0.834	0.776	0.798	0.734	0.790	0.796	0.790
		[0.011]	[0.016]	[0.041]	[0.083]	[0.059]	[0.106]	[0.064]	[0.046]	[0.066]
GRC	9	0.813	0.778	0.770	0.800	0.788	0.794	0.774	0.785	0.797
		[0.057]	[0.076]	[0.069]	[0.033]	[0.030]	[0.040]	[0.042]	[0.041]	[0.042]
ITA	14	0.743	0.771	0.688	0.720	0.726	0.707	0.740	0.755	0.737
		[0.107]	[0.089]	[0.139]	[0.106]	[0.097]	[0.109]	[0.100]	[0.094]	[0.097]
NLD	8	0.791	0.741	0.807	0.675	0.652	0.635	0.716	0.699	0.727
		[0.021]	[0.065]	[0.024]	[0.062]	[0.076]	[0.054]	[0.024]	[0.017]	[0.026]
PRT	8	0.665	0.638	0.683	0.564	0.624	0.543	0.589	0.626	0.567
		[0.123]	[0.139]	[0.097]	[0.096]	[0.080]	[0.095]	[0.122]	[0.118]	[0.125]
USA	275	0.867	0.823	0.884	0.710	0.692	0.704	0.771	0.780	0.773
		[0.053]	[0.072]	[0.038]	[0.092]	[0.097]	[0.089]	[0.087]	[0.102]	[0.090]

Model type:		Logistic Regression Model[b] (all countries)								
Dependent variable:		Open-Bank Assist.			Bank Closure			Bank Distress		
Estimation sample:	# Events[c]	All	EU	U.S.	All	EU	U.S.	All	EU	U.S.
Panel C: Use model score to predict **bank distress events** in...										
ALL	1203	0.693	0.826	0.520	0.862	0.844	0.860	0.875	0.864	0.873
		[0.037]	[0.015]	[0.085]	[0.031]	[0.032]	[0.032]	[0.023]	[0.021]	[0.022]
AUT	6	0.940	0.875	0.962	0.901	0.915	0.887	0.924	0.936	0.925
		[0.065]	[0.142]	[0.037]	[0.037]	[0.046]	[0.049]	[0.044]	[0.046]	[0.043]
DEU	23	0.535	0.589	0.497	0.887	0.846	0.873	0.859	0.830	0.785
		[0.091]	[0.084]	[0.093]	[0.058]	[0.060]	[0.064]	[0.061]	[0.057]	[0.093]
DNK	45	0.661	0.709	0.612	0.535	0.525	0.516	0.594	0.617	0.554
		[0.034]	[0.051]	[0.056]	[0.165]	[0.158]	[0.167]	[0.152]	[0.130]	[0.159]
ESP	31	0.777	0.815	0.700	0.902	0.923	0.885	0.899	0.905	0.889
		[0.040]	[0.044]	[0.037]	[0.053]	[0.052]	[0.046]	[0.037]	[0.037]	[0.030]
FRA	9	0.850	0.855	0.750	0.801	0.810	0.807	0.833	0.854	0.822
		[0.029]	[0.029]	[0.066]	[0.040]	[0.043]	[0.044]	[0.036]	[0.034]	[0.038]
GBR	32	0.743	0.724	0.761	0.744	0.755	0.712	0.743	0.722	0.748
		[0.047]	[0.045]	[0.049]	[0.046]	[0.046]	[0.048]	[0.050]	[0.052]	[0.049]
GRC	11	0.787	0.799	0.684	0.842	0.836	0.828	0.822	0.829	0.835
		[0.054]	[0.067]	[0.110]	[0.052]	[0.061]	[0.057]	[0.069]	[0.056]	[0.056]
IRL	7	0.582	0.575	0.594	0.562	0.581	0.543	0.587	0.557	0.579
		[0.054]	[0.040]	[0.076]	[0.118]	[0.133]	[0.093]	[0.091]	[0.086]	[0.091]
ISL	7	0.715	0.727	0.653	0.747	0.737	0.731	0.839	0.793	0.857
		[0.169]	[0.175]	[0.175]	[0.112]	[0.115]	[0.106]	[0.120]	[0.136]	[0.099]
ITA	62	0.685	0.736	0.630	0.821	0.817	0.811	0.818	0.810	0.815
		[0.069]	[0.043]	[0.085]	[0.025]	[0.028]	[0.022]	[0.028]	[0.030]	[0.027]
NLD	9	0.666	0.652	0.657	0.552	0.519	0.540	0.588	0.576	0.604
		[0.109]	[0.045]	[0.180]	[0.140]	[0.174]	[0.099]	[0.125]	[0.107]	[0.113]
PRT	11	0.632	0.604	0.646	0.644	0.683	0.624	0.620	0.641	0.607
		[0.082]	[0.099]	[0.070]	[0.101]	[0.064]	[0.110]	[0.093]	[0.068]	[0.101]
USA	941	0.704	0.848	0.482	0.886	0.878	0.884	0.897	0.892	0.898
		[0.043]	[0.017]	[0.120]	[0.046]	[0.047]	[0.047]	[0.033]	[0.029]	[0.033]

[a] This table presents the Areas Under ROC Curve (AUC) for predictors generated by a set of bank failure models, applied to predicting different types of bank distress events (1 year prediction horizon) within a set of 15 Western European Countries and the U.S. in the period 2006-2012.

[b] Each column in the table corresponds to the model that is used to generate bank distress predictions. Each model is a logistic regression using the same vector of covariates as models in Table 3.5. The models differ in the sample used to estimate the model (i.e Europe, U.S., or both) and in the event that serves as the dependent variable in the model estimation (i.e. bank closure, open-bank resolution, or a generally defined distressed event).

[c] In order to be included in the table, the number of events in a country must be larger than six.

[d] AUCs are obtained from the non-parametric ROC estimation, using bootstrap. For each country/predictor we report the estimated AUC and its standard error. The AUC may be interpreted as the probability that the randomly chosen distressed bank observation exhibits higher value of the predicted model score than the randomly chosen surviving observation.

We begin by noting several general patterns observed in Table 3.6:

- The best prediction of a given type of distress event is produced by the models that are built using the same type of distress event as the dependent variable. This result is unsurprising for the in-sample predictions where the estimation and the hold-out sample overlap. However, in most cases, the conclusion remains valid in the out-of-sample predictions. For example, the bank closure models estimated in Europe classify the U.S. bank closures with a similar level of accuracy than the bank closure models estimated in the U.S. (AUC of around 90%).

- Open-bank assistance models estimated on the European sample of banks have high accuracy in predicting bank closures in the U.S., with AUC of about 85%. This result is consistent with the conjecture that the bailed-out banks in Europe resemble the U.S. closed banks in the nature of their distress.

- Conversely, the U.S. open-bank assistance model, built primarily on TARP events, predicts the U.S. and European bank closures with only modest levels of accuracy.

- Open-bank assistance events are in general less predictable than the outright bank closures. Specifically, for bank closure and open-bank assistance events, the same-event AUCs are on average 90% and 80%, respectively.

- Bank closure models, both in the U.S. and Europe, predict open-bank assistance events with AUCs of about 70%, suggesting that the bank closure models are relatively ill-suited for identifying government recapitalizations of distressed banks.

We now turn to addressing the main question of this section, namely, assessing the extent to which bank distress is predictable by accounting fundamentals within specific countries. The main conclusions that emerge from Table 3.6 are as follows:

- Predictions generated by any given model display substantial cross-country variation in the accuracy of the within-country forecasts of any of the three types of bank distress events.

- Some of the countries with consistently low accuracy of distress predictions include Netherlands, Portugal, Ireland, and Denmark. In these countries, the accuracy of predictions in general does not exceed the AUC of 70%, and is, in many cases, close to the uninformative benchmark of 50%.

- Countries with consistently high levels of accuracy include the U.S., Austria, France, and Germany. The accuracy of predictions in these countries is typically above AUC of 80%.

Information content of the individual accounting ratios.

In order to examine the sources of poor predictive performance of the accounting-based models in some countries but not others, it is instructive to examine the informativeness of the individual accounting fundamentals that comprise the bank distress models, whose accuracy was estimated in the previous section.

For each of the 10 accounting fundamentals used in the models in Table 3.5 we proceed by computing the country-specific AUC from using the ratio in the prediction of generally-defined distress events (either closure or the open-bank resolution) within 1 year in the future. In Figure 3.2 we plot the resulting AUCs, together with the 95% confidence intervals, for each country and for each accounting fundamental.

The main conclusions from Figure 3.2 are summarized in the following points:

- The accounting variable that predicts bank distress with the highest level of accuracy and consistency across countries is Tier 1 regulatory capital ratio. The AUCs close to zero indicate that in most countries the randomly chosen distressed bank observations exhibit lower Tier 1 capital ratios than randomly chosen surviving observations. This is in line with the results in Table 3.5, in which the variation in Tier 1 capital is found to have the strongest economic impact on the probability of bank closure.

- Poor performance of the accounting-based models in countries like Luxembourg, Netherlands, Portugal, Ireland, and Denmark (see Table 3.6) appears to stem directly from the poor univariate predictive performance of the Tier 1 capital ratio (see Figure 3.2).

- Tier 2 capital ratio, asset risk weights, and unreserved impaired loans exhibit high cross-country variation in the accuracy of predicting bank distress.

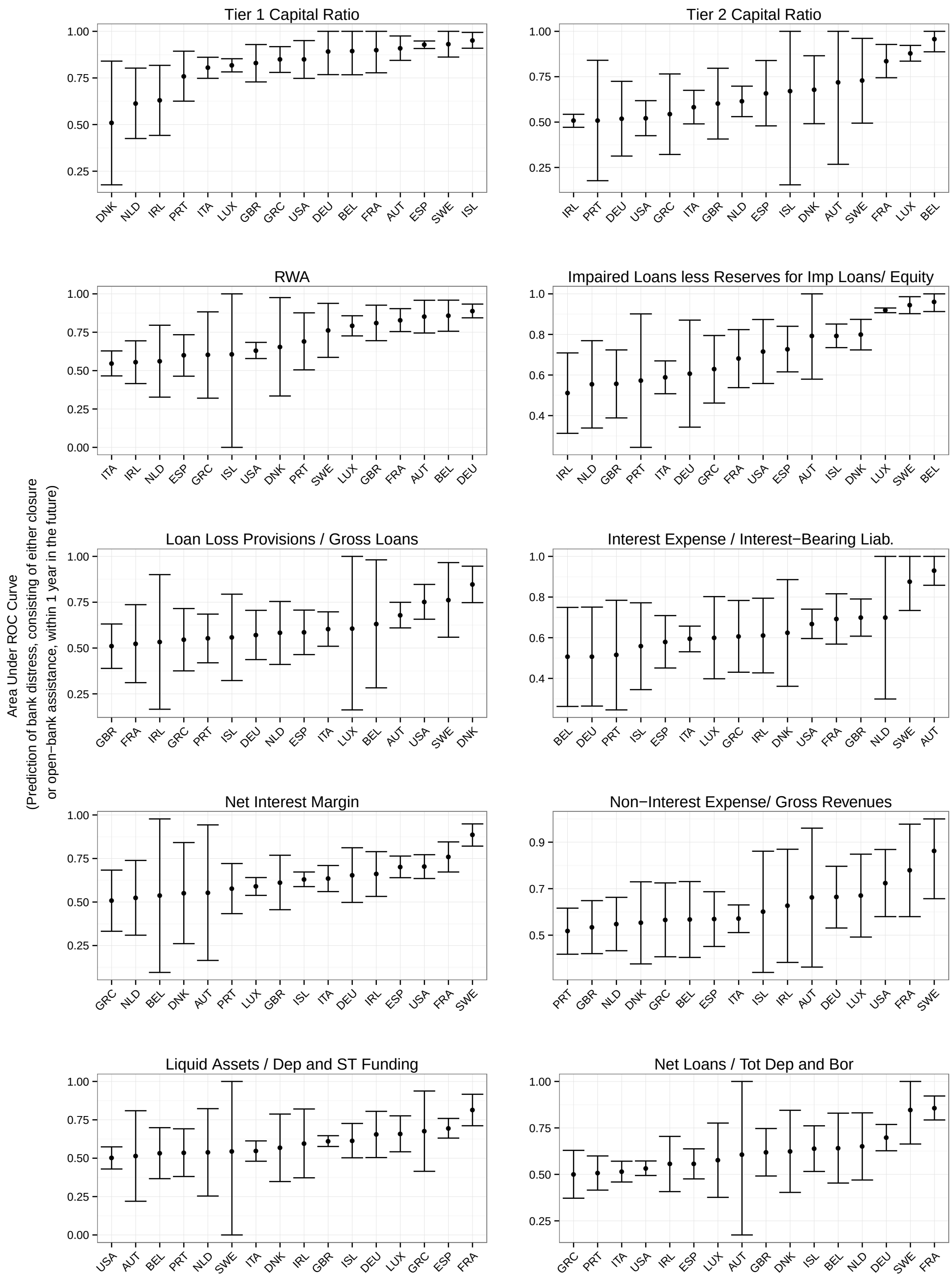


Figure 3.2 – Country-by-Country Areas under ROC Curve (AUC) for the Select Accounting Ratios. The figure shows the classification accuracy, measured by the AUC, in predicting bank distress (either closure or open-bank assistance) within 1 year in the future. AUCs are obtained from the non-parametric ROC estimation, using bootstrap. For each country/measure we report the estimated AUC and its 95% confidence interval. The AUC may be interpreted as the probability that the randomly chosen distressed bank observation exhibits higher value of the accounting ratio than the randomly chosen surviving observation.

3.4.2 How informative are the pre-crisis bank accounting figures in explaining the aggregate incidence of bank distress across countries during 2007-10?

In this section we examine an alternative way to measure the information content of accounting fundamentals. Specifically, we study whether the pre-crisis levels of the accounting fundamentals, when aggregated at the country level, explain the variation in the observed country level of bank distressed assets during the financial crisis episode.

Our main dependent variable of interest is the fraction of book assets attributable to banks that became distressed during the period 2008-10 relative to the total amount of banking sector book assets in the fiscal year-end of 2008[16], formally defined as:

$$FRAC\_DISTR_{c,[2008,2010]} = \frac{\sum_{i\in c \wedge i\in \text{Distressed}} \bar{A}_{i,t\in[2008,2010]}}{\sum_{i\in c} A_{i,t=2008}} \tag{3.4}$$

where A_i denotes the book value of bank i's assets, and c denotes a country. $FRAC\_DISTR$ is designed to proxy for the severity of a banking crisis at a country level, and it implicitly assumes an equal fractional impairment of distressed bank assets across countries. Countries with the largest fraction of bank assets in distress include Iceland, Greece, and Portugal, whereas the ones with the lowest observed bank distress rate include Luxembourg and Sweden.

Having defined the benchmark measure of country-wide bank distress, we now analyze the extent to which the variables that explain the within-country variation also explain the cross-country variation in bank distress.

First, we aggregate bank-level accounting variables, X_{ict}, into the country-level indicators, $\bar{X}_{ct}$, by weighting each bank-year observation of a variable by the bank's level of book assets (as a share of total banking assets in that country-year)[17]:

$$\bar{X}_{ct} = \sum_{i\in c} \frac{A_{ict}}{\sum_{i\in c} A_{ict}} X_{ict}. \tag{3.5}$$

Next, we investigate the extent to which pre-crisis accounting-based bank fundamentals anticipated the scale of country-specific bank distress in period 2008-2010

[16]The results of the analysis are robust to different choices of the base years for computing the aggregated banking sector assets.

[17]We also repeat entire analysis with equally weighted accounting fundamentals, and the main results remain qualitatively similar to the ones we report below.

by plotting each aggregated accounting measure, measured at the end of year 2006[18] (i.e. $\bar{X}_{c,2006}$) against $FRAC\_DISTR_{c,[2008-2010]}$. Figure 3.3 plots the result of the exercise. Before interpreting the results, one should be mindful of the somewhat low number of countries in the study (i.e. 15 Western European countries and the U.S.), and all the caveats that pertain to drawing conclusions from small samples of observations. That said, we believe that studying cross-country patterns of bank accounting ratios in the context of the recent banking crisis is instructive in elucidating their ability to capture risks at the country level.

Several observations emerge from Figure 3.3. First, reported Tier 1 and Tier 2 regulatory capital ratios (reported as a fraction of risk-weighted assets) serve as poor predictors of banking problems at the country level. If anything, banks in countries with high rates of distress in 2008-10 report on average higher levels of both forms of regulatory capital in years preceding the crisis. In principle, this pattern could emerge simply as a result of banks in ex-post riskier countries recognizing their higher risk of distress already in 2006, and anticipating this risk by holding additional regulatory capital. Indeed, the plot of reported risk-weighted assets in Figure 3.3 reveals that banks in countries with high observed level of distress on average reported significantly higher asset risk-weights in 2006. In unreported country-level regressions, which control for the bank asset risks, the sign of Tier 1 capital ratio becomes negative, but is statistically insignificant, with p-value of 65%.

A second conclusion that can be drawn from Figure 3.3 is that, apart from the reported asset risk weights, the only bank accounting-based aggregate in 2006 that exhibits a clear relation with the ex-post bank distress in 2008-10 is the net-interest margin. Specifically, countries with banks that reported on average higher net-interest margins in 2006 experienced higher incidence of bank distress during 2008-10.

3.5 Bank Disclosure Quality

The main conclusion that emerges from the analyses in Sections 3.4.1 and 3.4.2 is that predictability of bank distress by accounting fundamentals varies substantially across countries. This section takes a closer look at variations in the informativeness of bank accounting and examines the extent to which such variations are explained by national bank disclosure standards and their enforcement by the regulators.

[18] We repeat the analysis by using the 2007 fiscal-year results and the results remain qualitatively unchanged.

To motivate the analysis, it should first be noted that the state of bank financial condition, especially for non-listed banks, is predominately inferred from bank accounting disclosure. Bank management possesses substantial discretion over multiple reporting attributes, and consequently has the capacity to report inaccurate information. Apart from having the *capacity* to hide bad performance, a compelling case can be made that banks, especially the ones in the lower tail of performance distribution, also have *incentives* to use accounting discretion to improve their reported performance. Specifically, a bank close to distress may use accounting discretion to improve its reported regulatory capital ratio in order to avoid negative attention of its regulator, or to avoid a run on its funding.

To the extent that banks in financial distress are more likely to use accounting discretion to improve their reported performance relative to their healthier peers, the ability of the accounting numbers to discriminate between distressed and non-distressed banks is necessarily reduced. In the extreme case, in which the reported accounts of the distressed and non-distressed banks are indistinguishable, the information value of the accounting fundamentals in prediction of distress is essentially non-existent.

A combination of reporting discretion and the incentives to use it is particularly acute in the following areas of bank disclosure: (1) computation of regulatory capital, (2) computation of asset risk weights, (3) accounting for losses, and (4) loan loss provisioning. For example, management can improve the reported regulatory capital ratio by delaying recognition of loan impairments[19], by counting as capital the hybrid instruments with poor loss-absorption qualities, or by underweighting risks of certain assets in the computation of risk-weighted assets (RWA), the denominator in the regulatory capital ratio formula. The latter is of a particular concern, because after the enactment of Basel II most banks compute their risk weights according to their internal rating-based approaches[20], which allows for a substantial degree of flexibility.

In principle, bank disclosure standards and their enforcement by regulators provide a constraint on banks' accounting discretion and on their information revelation incentives. Banks in jurisdictions with more restrictive disclosure laws, or with more diligent supervisory enforcement of the stated standards, are presumably less willing and able to engage in accounting manipulation to hide poor performance. Obviously,

[19] Recognition of loan impairments may be delayed by a bank rolling-over their non-performing loans.

[20] The main benefit of the IRB approach is that in principle it allows for a more accurate measurement of bank risks. However, degrees of freedom inherent in this approach, give banks a leeway to misrepresent their financial health.

low levels of discretion and strong supervisory enforcement come at a cost. First, by potentially decreasing the informativenenss of accounting reports by banks that are not in distress, and second, by draining limited supervisory resources.

As we show below, countries in our sample exhibit substantial variations in proxies of bank accounting discretion and regulatory enforcement stringency. Following the previous line of reasoning, such variations could conceivably influence the informativeness of accounting ratios in bank distress prediction. Our objective in the remainder of this section is to examine whether and how different bank disclosure regimes influence the informativeness of accounting fundamentals.

3.5.1 Measurement of Bank Disclosure Standards and Their Enforcement by the Regulators

We obtain a set of proxy measures of country-specific bank disclosure quality from the database of Barth et al. (2013), who compile a set of more than 50 different indices from the quadrennial World Bank surveys covering 180 countries since 1999. The indices in their database measure several different aspects of domestic bank regulation, including capital regulation, disclosure and monitoring environment, failed bank resolution, bank competition, and supervisory structure. In the following analysis we only use the subset of indices measuring the quality of countries' disclosure and monitoring environment. Descriptions of the indices can be found in Table 3.7. Each index is standardized according to the following formula:

$$R_c^* = \frac{R_c - min(R)}{max(R) - min(R)} \in [0, 1],$$

where R_c is the raw value of the index for country c, and $min(R)$/ $max(R)$ represent minimum/maximum value of the index in the entire database of 180 countries across all times. The index value for each country is averaged over the period 2007-2012. For each index, higher values of the index correspond to either better disclosure standards, or a more stringent implementation of the standards by the regulator. Values of the standardized indices for each country are presented in Figure 3.4.

Table 3.7 – Definition of Regulatory Indices from Barth et al. (2013)

Index Name	Description
Accounting Practices	The type of accounting practices used (higher values indicate better practices).
Bank Accounting	Measures whether the income statement includes accrued or unpaid interest or principal on nonperforming loans and whether banks are required to produce consolidated financial statements (higher values indicate more informative accounts).
Certified Audit Required	Measures the presence of a requirement of a compulsory external audit by a licensed or certified auditor,
External Ratings and Creditor Monitoring	Captures the extent of evaluations by external rating agencies and incentives for creditors of the bank to monitor bank performance (higher values indicate better creditor monitoring).
Private Monitoring Index	Measures whether there are incentives for private monitoring of firms, with higher values indicating more private monitoring.
Overall Capital Stringency	Measures whether the capital requirement reflects certain risk elements and deducts certain market value losses from capital before minimum capital adequacy is determined (higher values correspond to greater stringency).
Capital Regulatory Index	Similar to the "overall capital stringency", except that it also measures whether certain funds may be used to initially capitalize a bank (higher values correspond to greater stringency).

Notes:
[a] This table defines the bank regulatory disclosure proxies used in the paper. The regulatory indices come from the database of Barth et al. (2013).

3.5.2 Test 1: Bank Disclosure Quality and Accounting Information Content in a Cross-Section of Banks

We next examine the association between country-specific quality of disclosure, R, and a cross-sectional measure of accounting informativeness.

We measure the information of content of an accounting fundamental, x, as the absolute magnitude of the marginal impact of x on the probability that a bank becomes distressed 1 year in the future, within a cross section of banks in country c at time t:

$$INFO_{ct}(x) = \left\| \left. \frac{\partial Pr(\text{Distressed}_{ict} = 1)}{\partial x_{ict}} \right|_{\text{c,t fixed}} \right\|$$

The intuition of the measure is simple: the information value of an accounting fundamental increases with its ability to identify distress in a cross section of banks in a given country-year. In line with the discussion above we expect the informativeness of an accounting measure to be greater in countries with more stringent standards or with more vigilant implementation of the standards by the regulators. Following the previous notation, this can be stated as:

$$INFO_{ct}(x)\Big|_{\substack{\text{c,t fixed} \\ c \in \text{Good Disclosure Country}}} > INFO_{ct}(x)\Big|_{\substack{\text{c,t fixed} \\ c \in \text{Bad Disclosure Country}}} \geq 0 \tag{3.6}$$

Eq. 3.6 implies that the marginal contribution of accounting ratio x in bank distress prediction is a function of the regulatory index, R. In the context of the framework introduced in Section 3.3.2, we can test this implication by interacting the accounting ratio x with the value of R:

$$\begin{aligned} Pr(\text{Distressed}_{ict} = 1) &= \text{Logit}(\alpha_{ct} + x'_{ict}\theta + \epsilon_{ict}) \\ &= \text{Logit}(\alpha_{ct} + x_{ict} * (\phi_1 + \phi_2 R_{ct}) + \epsilon_{ict}) \\ &= \text{Logit}(\alpha_{ct} + \phi_1 * x_{ict} + \phi_2 * R_{ct} * x_{ict} + \epsilon_{ict}) \end{aligned} \tag{3.7}$$

where α_{ct} controls for country-year specific trends, x_{ict} is one of the bank-specific accounting measures of interest, and R denotes a country-specific proxy for regulatory disclosure and monitoring requirements. The hypothesis in Eq. 3.6 implies that $|\phi_1 + \phi_2| > |\phi_1|$. To see this, notice that a sum of ϕ_1 and ϕ_2 represents the marginal contribution of an accounting ratio to the log-odds of distress in countries with most stringent disclosure laws and their implementation (i.e. $R_{ct} = 1$). Conversely, ϕ_1 represents a marginal contribution in countries with weak bank disclosure environment (i.e. $R_{ct} = 0$). The hypothesis in Eg. 3.6 postulates that the absolute marginal contribution of an accounting ratio is stronger in countries with stringent bank disclosure environment, hence $|\phi_1 + \phi_2| > |\phi_1|$.

Notice that the hypothesis in Eg. 3.6 does not postulate the *direction* of the correlation between the accounting signal and bank distress, but concerns only the *magnitude* of the correspondence. The implications of the hypothesis can be nuanced further, by taking into account the direction of the associations between bank distress and fundamentals, predicted by the banking theory. Theoretically, one expects to observe a negative association between bank distress and bank capital (both Tier 1 and Tier 2), and a positive association between bank distress and RWA, unreserved impaired loans, and loan loss provisions. We expect the theoretically predicted *direction* of the correspondence to be stronger in countries with better disclosure laws, which implies a negative interaction term, θ_2, for bank capital, and a positive interaction term for RWA, unreserved impaired loans, and loan loss provisions.

Table 3.8 reports the estimates of the specification of Eq. 3.7. We separately estimate the specification for five accounting ratios that are often considered as the most prone to manipulation, namely: (1) Tier 1 capital ratio, (2) Tier 2 capital ratio, (3) risk-weighted assets[21], (4) unreserved loan losses, and (5) loan loss provisions. Columns 1-7 report the estimates for the regressions with regulatory interactions for each of the disclosure and monitoring indices described in Section 3.5.1[22]. Estimates reported in different panels of Table 3.8 come from separate estimations of specification in Eq. 3.7. Since our regulatory variables are standardized to lie in the range between 0 (worst disclosure quality) and 1 (best disclosures quality), the interpretation of the interaction term coefficient is straightforward: it represents a change in the marginal contribution of the accounting fundamental on the probability of bank distress as one moves from the worst-disclosure jurisdiction to the best-disclosure jurisdiction.

[21] As before, we scale the reported risk-weighted assets by the total book values of assets. The resulting measure may be interpreted as the aggregate (at the bank level) asset risk weight.

[22] The seven regulatory indices exhibit high levels of positive pairwise correlations (with Pearson correlation coefficients above 0.6). As a result, estimation of a specification that includes the interactions with all regulatory indices is infeasible due to multicollinearity.

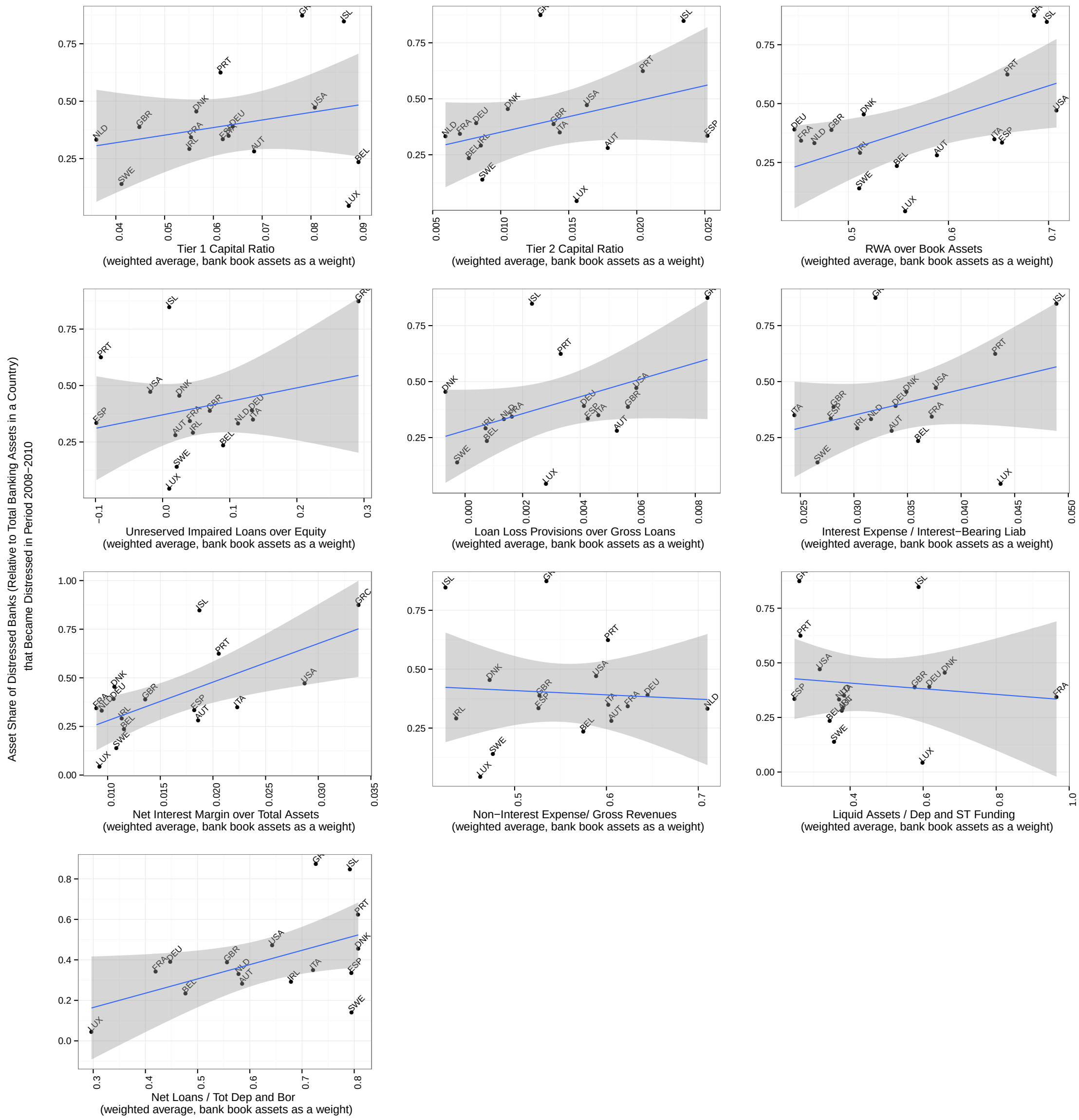


Figure 3.3 – The figure plots $FRAC\_DISTR$, a country-wide measure of severeity of bank distress during the period 2008-10, against a set of aggregated bank accounting measures, used in the analysis of within-country variation in bank distress. $FRAC\_DISTR$ is defined as: $FRAC\_DISTR_{c,[2008,2010]} = \frac{\sum_{i \in c \wedge i \in \text{Distressed}} \bar{A}_{i,t\in[2008,2010]}}{\sum_{i \in c} A_{i,t=2008}}$, where A_i denotes the book value of bank i's assets, and c denotes a country. We aggregate bank-level accounting variables, X_{ict}, into the country-level indicators, $\bar{X}_{ct}$, by weighting each bank-year observation of a variable by the bank's level of book assets (as a share of total banking assets in that country-year): $\bar{X}_{ct} = \sum_{i \in c} \frac{A_{ict}}{\sum_{i \in c} A_{ict}} X_{ict}$.

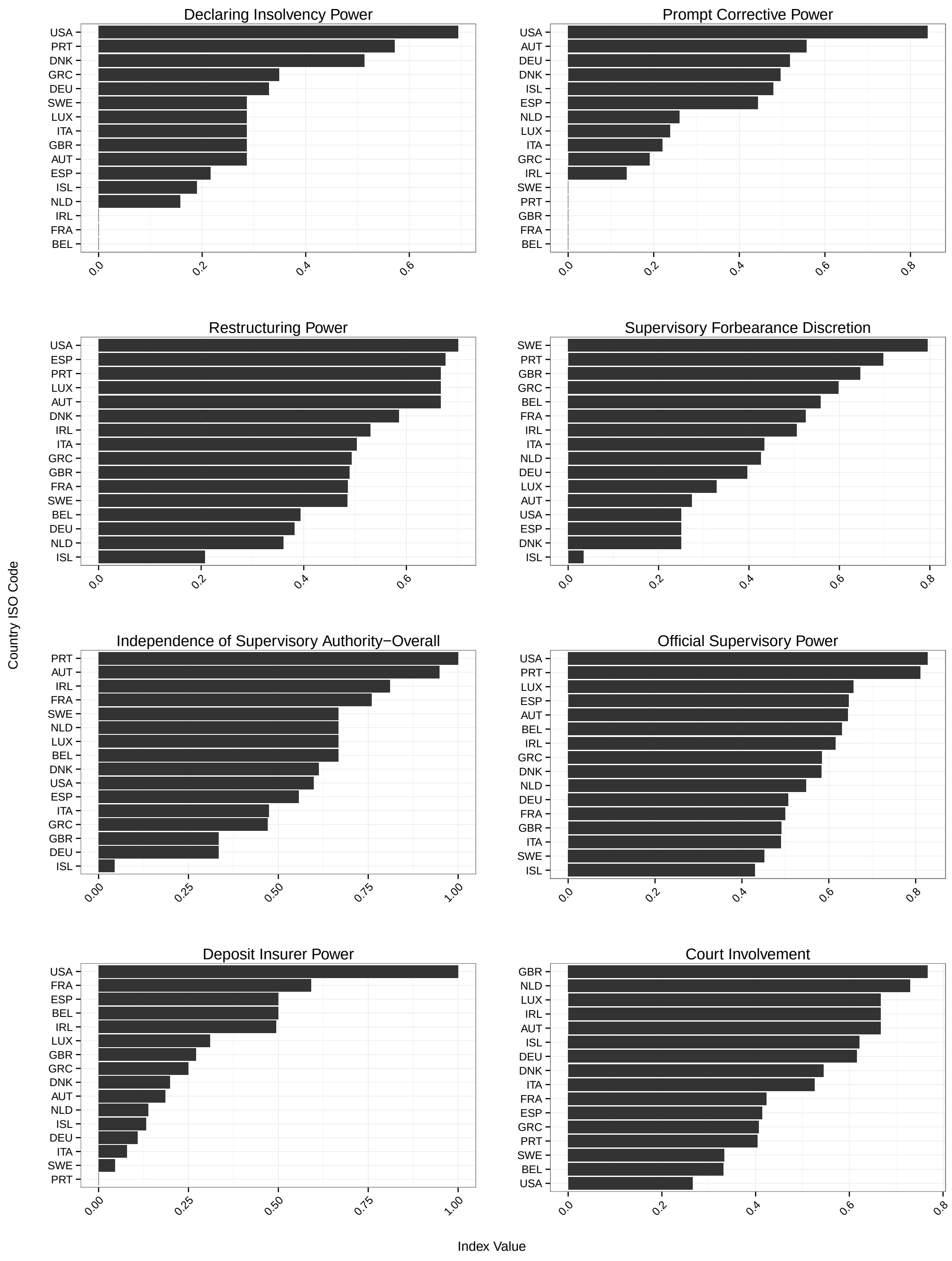


Figure 3.4 – Bank Regulation across Countries: Bank Disclosure. The figure plots the regulatory indices from the database of Barth et al. (2013). Each index is standardized according to the following formula: $X_c^* = \frac{X_c - min(X)}{max(X) - min(X)} \in [0, 1]$, where X_c is the raw value of the index for country c, and $min(X)/\ max(X)$ represent minimum/maximum value of the index in the entire database of 180 countries across all times. The index value for each country is averaged over the period 2007-2012.

Table 3.8 – Within-Country Cross-Sectional Evidence on the Association between Accounting Informativeness and Bank Disclosure Quality

	Type of Regulatory Index:						
	(1) Accounting Practices	(2) Bank Accounting	(3) Certified Audit Required	(4) External Ratings and Creditor Monitoring	(5) Private Monitoring Index	(6) Capital Regulatory Index	(7) Overall Capital Stringency
θ_1: Regulatory Tier 1 Ratio	-3.20***	-0.44	-3.58***	0.10	-1.31**	1.64***	0.69
	[0.45]	[0.88]	[0.50]	[0.54]	[0.66]	[0.47]	[0.46]
θ_2: Regulatory Tier 1 Ratio * [Regulatory Index]	-0.71	-3.62***	-0.29	-5.58***	-3.17***	-8.91***	-6.68***
	[0.47]	[0.93]	[0.52]	[0.75]	[0.81]	[0.77]	[0.68]
Test: $\lvert\theta_1 + \theta_2\rvert - \lvert\theta_1\rvert > 0$	1	1	1	1	1	1	1
P-value	0.07	0.00	0.29	0.00	0.00	0.00	0.00
θ_1: Regulatory Tier 2 Ratio	0.27**	-0.62**	0.50***	0.66***	0.62**	0.29	0.57***
	[0.12]	[0.29]	[0.15]	[0.20]	[0.25]	[0.19]	[0.20]
θ_2: Regulatory Tier 2 Ratio * [Regulatory Index]	-0.28**	0.95***	-0.51***	-0.99***	-0.81**	-0.43	-0.87***
	[0.14]	[0.31]	[0.16]	[0.33]	[0.35]	[0.33]	[0.32]
Test: $\lvert\theta_1 + \theta_2\rvert - \lvert\theta_1\rvert > 0$	0	0	0	0	0	0	0
P-value	0.97	0.86	1.00	0.99	0.99	0.87	0.97
θ_1: RWA over Book Assets	-0.51***	-2.23***	-0.25*	-0.98***	-1.61***	-0.17	-0.19
	[0.17]	[0.33]	[0.14]	[0.21]	[0.26]	[0.19]	[0.18]
θ_2: RWA over Book Assets * [Regulatory Index]	0.69***	2.56***	0.45***	1.67***	2.25***	0.53*	0.60**
	[0.18]	[0.35]	[0.16]	[0.30]	[0.32]	[0.32]	[0.26]
Test: $\lvert\theta_1 + \theta_2\rvert - \lvert\theta_1\rvert > 0$	0	0	0	0	0	1	1
P-value	0.96	1.00	0.64	0.97	1.00	0.06	0.05
θ_1: Impaired Loans less Reserves for Imp Loans/ Equity	0.43***	-1.01**	0.48***	-0.63***	-0.38*	0.04	0.29**
	[0.17]	[0.40]	[0.12]	[0.24]	[0.22]	[0.17]	[0.13]
θ_2: Impaired Loans less Reserves for Imp Loans/ Equity * [Regulatory Index]	0.39**	1.85***	0.34***	1.87***	1.39***	1.15***	0.70***
	[0.17]	[0.40]	[0.12]	[0.30]	[0.25]	[0.25]	[0.17]
Test: $\lvert\theta_1 + \theta_2\rvert - \lvert\theta_1\rvert > 0$	1	0	1	1	1	1	1
P-value	0.01	0.68	0.00	0.00	0.00	0.00	0.00
θ_1: Loan Loss Provisions / Gross Loans	0.18*	-0.81***	0.31***	-0.55***	-0.48**	0.22*	0.38***
	[0.10]	[0.28]	[0.11]	[0.21]	[0.21]	[0.13]	[0.12]
θ_2: Loan Loss Provisions / Gross Loans * [Regulatory Index]	0.36***	1.40***	0.20*	1.42***	1.22***	0.43**	0.16
	[0.10]	[0.29]	[0.11]	[0.28]	[0.25]	[0.20]	[0.16]
Test: $\lvert\theta_1 + \theta_2\rvert - \lvert\theta_1\rvert > 0$	1	0	1	1	1	1	1
P-value	0.00	0.77	0.50	0.02	0.06	0.02	0.16

Notes:
[a] The table reports the estimation coefficients of the interaction terms in the following specification:

$$Pr(D_{ict} = 1) = \text{Logit}(\alpha_{ct} + \theta_1 * x_{ict} + \theta_2 * R_{ct} * x_{ict} + \epsilon_{ict}) \tag{3.8}$$

where $D_{i,c,t}$ is the indicator of a bank becoming distressed within 1 year from the publishing of the accounting information, and i, c, and t denote firm, country, and time indices, respectively.
[b] R_{ct} is one of seven regulatory indices, obtained from the database of Barth et al. (2013), who construct the indices from quadrennial World Bank surveys covering 180 countries since 1999. Definitions of the indices used in our paper are given in Table 3.7.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Results are consistent with the disclosure-quality hypothesis for Tier 1 regulatory capital ratio, unreserved loan losses and loan loss provisions. In each of the cases, an accounting signal of bank distress tends to be stronger in countries with strong disclosure laws and/or with more stringent enforcement of the existing laws. Additionally, the direction of the accounting signal in each of the three cases is consistent with the theoretical prior. Specifically, Tier 1 regulatory capital ratio exhibits a negative relation with bank distress, whereas the unreserved loan losses and the loan loss provisions exhibit a positive association.

In the cases of the Tier 2 regulatory capital ratio and the RWA ratio, the association between accounting signals and bank distress shifts in the direction of the theoretical prior as one moves to the jurisdictions with more stringent disclosure environments. In particular, both Tier 2 capital ratio and the RWA have a theoretically counter-intuitive correspondence with bank distress in countries with poor disclosure quality, and a theoretically predicted correspondence in countries with better disclosure quality.

Table 3.9 – Within-Firm/Time-Series Evidence on the Association between Accounting Informativeness and Bank Disclosure Quality

	Type of Regulatory Index:						
	(1) Accounting Practices	(2) Bank Accounting	(3) Certified Audit Required	(4) External Ratings and Creditor Monitoring	(5) Private Monitoring Index	(6) Capital Regulatory Index	(7) Overall Capital Stringency
θ_1: Regulatory Tier 1 Ratio	-8.95***	-2.80**	-7.00***	0.92	-5.00**	-1.78*	-1.98**
	[1.13]	[1.38]	[1.99]	[1.30]	[2.07]	[0.95]	[0.86]
θ_2: Regulatory Tier 1 Ratio * [Regulatory Index]	3.14***	-3.01**	1.31	-9.09***	-0.77	-5.43***	-4.54***
	[1.05]	[1.41]	[1.99]	[1.78]	[2.45]	[1.43]	[1.18]
Test: $\|\theta_1 + \theta_2\| - \|\theta_1\| > 0$	0	1	0	1	1	1	1
P-value	1.00	0.02	0.75	0.00	0.38	0.00	0.00
θ_1: Regulatory Tier 2 Ratio	0.42**	1.33**	0.16	1.71***	3.97***	1.93***	2.03***
θ_2: Regulatory Tier 2 Ratio * [Regulatory Index]	-0.86***	-1.67***	-0.37	-2.84***	-5.48***	-3.50***	-3.21***
Test: $\|\theta_1 + \theta_2\| - \|\theta_1\| > 0$	1	0	1	0	0	0	0
P-value	0.48	0.96	0.46	0.93	1.00	0.91	1.00
θ_1: RWA over Book Assets	-1.24***	-1.78***	-0.51*	0.46	-0.19	-1.07***	-0.58**
	[0.26]	[0.57]	[0.27]	[0.52]	[0.70]	[0.31]	[0.29]
θ_2: RWA over Book Assets * [Regulatory Index]	0.37	1.01*	-0.33	-1.85**	-0.85	0.08	-0.73*
	[0.24]	[0.57]	[0.29]	[0.73]	[0.87]	[0.49]	[0.43]
Test: $\|\theta_1 + \theta_2\| - \|\theta_1\| > 0$	0	0	1	1	1	0	1
P-value	0.94	0.96	0.13	0.01	0.17	0.57	0.04
θ_1: Impaired Loans less Reserves for Imp Loans/ Equity	1.57***	0.67	1.73***	-0.02	0.39	1.69***	1.34***
θ_2: Impaired Loans less Reserves for Imp Loans/ Equity * [Regulatory Index]	-0.13	0.84	-0.27	1.98**	1.30**	-0.62	-0.15
Test: $\|\theta_1 + \theta_2\| - \|\theta_1\| > 0$	0	1	0	1	1	0	0
P-value	0.65	0.09	0.73	0.00	0.01	0.91	0.69
θ_1: Loan Loss Provisions / Gross Loans	0.46**	-0.84	0.97**	0.24	-0.23	3.28***	3.04***
	[0.19]	[0.55]	[0.40]	[0.38]	[0.56]	[0.38]	[0.33]
θ_2: Loan Loss Provisions / Gross Loans * [Regulatory Index]	0.73***	2.08***	0.18	1.21**	1.67**	-3.46***	-2.81***
	[0.20]	[0.57]	[0.40]	[0.51]	[0.67]	[0.57]	[0.46]
Test: $\|\theta_1 + \theta_2\| - \|\theta_1\| > 0$	1	1	1	1	1	0	0
P-value	0.00	0.24	0.33	0.01	0.00	1.00	1.00

Notes:
[a] The table reports the estimation coefficients of the interaction terms in the following specification:

$$Pr(D_{ict} = 1) = \text{Logit}(\alpha_i + \theta_1 * x_{ict} + \theta_2 * R_{ct} * x_{ict} + \epsilon_{ict}) \tag{3.9}$$

where $D_{i,c,t}$ is the indicator of a bank becoming distressed within 1 year from the publishing of the accounting information, and i, c, and t denote firm, country, and time indices, respectively.
[b] R_{ct} is one of seven regulatory indices, obtained from the database of Barth et al. (2013), who construct the indices from quadrennial World Bank surveys covering 180 countries since 1999. Definitions of the indices used in our paper are given in Table 3.7.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

3.5.3 Test 2: Disclosure Quality and Accounting Informativeness: Within-Firm (Time-Series) Evidence

An alternative way to assess the informativeness of accounting reports is to examine whether a time series of accounting signals produced by a distressed bank anticipates the bank's eventual failure. Following the nomenclature of the previous section, the informativeness of an accounting fundamental, x, is now defined as the marginal impact of x, reported by bank i, on the probability that bank i becomes distressed 1 year in the future:

$$INFO_{ic}(x) = \left\| \left. \frac{\partial Pr(\text{Distressed}_{ict} = 1)}{\partial x_{ict}} \right|_{\text{i fixed}} \right\|$$

The intuition of the measure is as follows: the information value of an accounting fundamental increases with the ability of its time-series movements to anticipate eventual distress of the reporting institution. To illustrate, if a bank, which eventually becomes distressed, reports the same value of an accounting fundamental in all periods leading up to a distress event, the accounting signal is judged as uninformative according to the above definition. On the other hand, the signal is judged as informative if its reported value immediately before the distress period is distinct from its value in the periods further from the distress event.

As before, we expect the informativeness of an accounting measure to be greater in countries with more stringent standards or with more vigilant implementation of the standards by the regulators:

$$INFO_{ic}(x)\Bigg|_{\substack{\text{i fixed} \\ c\in\text{Good Disclosure Country}}} > INFO_{ic}(x)\Bigg|_{\substack{\text{i fixed} \\ c\in\text{Bad Disclosure Country}}} \geq 0 \qquad (3.10)$$

We test the above prediction by estimating the following specification (notice the inclusion of firm-fixed effects):

$$Pr(\text{Distressed}_{ict} = 1) = \text{Logit}(\alpha_i + \phi_1 * x_{ict} + \phi_2 * R_{ct} * x_{ict} + \epsilon_{ict}). \qquad (3.11)$$

The above specification is estimated only on the subsample of banks that become distressed at some point in the sample. The main difference between Eq. 3.7 and Eq. 3.11 is that the latter exploits the within-firm variation to estimate the coefficients, whereas the former relies on the within-country/year variation.

Table 3.9 shows the results of the within-firm estimation. The main conclusions are similar to the previous section. The informativeness of the Tier 1 capital ratio, unreserved loan losses, and loan loss provisions tends to be greater in countries with better disclosure quality. On the other hand, the disclosure-contingent reversion in the association between bank distress and Tier 2 capital is even more pronounced within a firm than in a cross section. Specifically, prior to their distress event, banks in countries with low disclosure quality tend to increase their Tier 2 capital whereas their counterparts in countries with better disclosure quality tend to decrease the reported levels of Tier 2 capital.

3.6 Concluding Remarks

This article provides a comprehensive account and analysis of bank failures in the U.S. and Western Europe during the recent financial crisis. The major contribution of our paper is to provide an in-depth examination of the information content of the accounting fundamentals and to study the relation between the observed variations in accounting informativeness and the stringency of bank disclosure standards and their enforcement by regulators.

We show that predictions generated by accounting-based models display a substantial cross-country variation in bank distress classification performance. We also demonstrate that the pre-crisis values of accounting fundamentals, aggregated at the country level, fail to explain the 2007-10 aggregate incidence of bank distress across countries. We show that the informativeness of accounting fundamentals in the cross section of banks in a given country-year positively correlates with the quality of accounting standards and the stringency of their enforcement. In particular, accounting signals of bank distress tend to be stronger in countries with strong disclosure laws or with more stringent enforcement of the existing laws. We also show that the disclosure-quality/information content nexus continues to hold when looking at the informativeness of the time series movements in accounting fundamentals for distressed banks prior to the distress event.

A combination of reporting discretion and the incentives of distressed banks to use accounting discretion to improve the reported performance in order to avoid negative regulatory action or deposit runs, will decrease the informativeness of accounting fundamentals. In the case of an extreme 'signal-jamming', a distressed bank may report performance that mimics the performance of its non-distressed peers, thus essentially nullifying the information value of the accounting signal.

Given that investors and regulators typically learn about banks' financial condition from the banks' public disclosures, our results have clear implications for bank disclosure regulation. The evidence in this paper supports the oft-voiced concern that excessive flexibility in financial reporting undermines the ability of accounting signals to accurately capture the underlying financial health of banks. Obliqueness of the distressed s accounting signals makes such information less useful for investors and regulators, and thus has negative regulatory implication. Perhaps the main implication of this conclusion is that the information content of accounting fundamentals, at least with respect to the identification of distressed banks, will be improved by increased stringency of bank disclosure laws and their enforcement.

CHAPTER 4

Assessing Basel III Capital Ratios: Do Risk Weights Matter?

[1] *"Marking your own exams is a perilous pursuit."*

— Andrew G. Haldane (2013)[2]

"Paradox of instability: the financial system can appear strongest precisely when it is most fragile. "

— Borio and Drehmann (2009)

4.1 Introduction

The Basel III agreements (see BCBS, 2008, 2010, 2011) were designed to address the inadequacies of the existing Basel II framework, exposed by the widespread financial turmoil following the financial meltdown in 2008. The prevailing view underlying the changes in Basel regulation is that the recent financial disruptions in the Western banking systems stem from the interplay of the following major factors: (1) insufficient capitalization - both in terms of quantity and quality of capital - that failed to capture the build-up of on-and-off-balance sheet risks, (2) excessive maturity mismatch, driven by bank funding structures biased towards short-term funding sources, and (3) insufficient holding of high quality liquid assets that would

[1] This chapter is based on Cizel and Rijken (2016), co-authored with Professor Herbert A. Rijken (*Vrije Universiteit Amsterdam*).

[2] From the speech, titled "Constraining discretion in bank regulation". Available at: http://www.bankofengland.co.uk/publications/Documents/speeches/2013/speech657.pdf

allow financial institutions to independenty cope with short-term funding squeezes, and (4) materialization of unforeseen systemic risks.

Basel III regulation attempts to address these shortcomings by updating the existing capital regulation, as well as by introducing minimum liquidity standards, a hitherto uncharted territory in the previous Basel accords. With respect to the capital regulation, it aims to increase the quantity and quality of bank capital buffers by: (1) raising the minimum level of core Tier 1 equity capital, (2) introducing an additional capital conservation buffer and a countercyclical buffer, (3) increasing the quality of the capital base by requiring intangible assets such goodwill and deferred taxes to be deducted from regulatory capital, and (4) improving risk coverage by proposing a stronger capital treatment of securitisation and trading book exposures, as well as by stipulating more stringent requirements pertaining to counterparty credit risk. It also aims to improve systemic resilience by introducing a leverage ratio (LR) requirement (ESRB, 2016; ESRB, 2015) and additional capital requirements for systemically important financial institutions (SIFI).

With regard to liquidity regulation, Basel III introduces two new liquidity ratios: (1) the liquidity coverage ratio and (2) the net stable funding ratio. The former focuses on the ability of banks to meet short-term cash outflows in stressed funding conditions, and the latter is a longer term structural ratio that measures the liquidity mismatches of the entire bank balance sheet. The proposed liquidity regulation stipulates that banks hold a minimum level of both ratios, and hence gives banks an incentive to mobilize more stable funding sources. For a comprehensive discussion of liquidity requirements in the context of Basel regulation, see Bonner, Hilbers, and van Lelyveld (2015, Chapter 2).

While the motivations behind the changes in Basel III are widely accepted, some of its underlying premises have not been tested extensively by the literature. This is the area to which this chapter aims to make a contribution.

Specifically, it focuses on the capital-related regulations of Basel III and empirically examines three sets of assumptions that are implicit in Basel III capital regulation: (1) distress-relevance of bank regulatory capital, (2) poor loss-absorption properties of intangibles, such as deferred tax assets (DTAs) and goodwill, and (3) backstop property of risk-insensitive regulatory capital measures. Since each of these assumptions has empirical implications regarding the predictability of bank distress, we use the EWS framework for banks developed in Chapter 3 to test their validity. Specifically, we construct a series of tests that study the extent to which measures, derived from Basel III, explain distress events in a panel of Western European and the US banks around the GFC.

Our key finding is on the information value of Basel risk weights (RWs[3]) in the context of predicting bank distress. Specifically, we show that the association between RWs and bank distress is significant only in the subset of small (non-IRB) banks, while it is statistically insignificant for the large (IRB) banks. This finding is consistent with a concern that the IRB banks may apply discretion in ways that hamper the association between their *reported* and real risks.

We provide further evidence in support of this explanation by showing that in response to the negative capital shocks, RWs of large (IRB) banks tend to fall, thus mitigating the effect of the shock on the banks' risk-weighted capital ratio (RWCR). We show that the downward movement in RWs attenuates the effect of a capital shock on the IRB bank's RWCR by 0.3pp for each 1pp fall in bank capital. In contrast, we show that for the small (non-IRB) banks, which have less discretion in reporting their RWs, the relationship between the negative capital shocks and RW is significantly weaker or disappears.

The overall evidence presented in this chapter highlights the discrepancy between banks' *reported* capital and its economic (conceptual) counterpart, especially in the case of the IRB banks. This confirms the concerns that have led to the recent regulatory push towards (1) improving the quality composition of regulatory capital and (2) increasing reliance on *risk-insensitive* measurement of bank capital, encapsulated in the LR.

This study is not the first to highlight the potential problems with the risk-sensitive approach of Basel II. In this regard, our findings complement at least two strands of recent literature. The first consists of studies that empirically compare the performance of risk-sensitive and risk-insensitive capital measures. Studies like Aikman et al. (2014), Berger and Bouwman (2013), Haldane and Madouros (2012), and Mayes and Stremmel (2012) find that risk-insensitive capital measures often out-perform risk-sensitive measures in predicting bank default. Risk insensitive capital measures also appear to be better predictors of future bank stock market performance (Blundell-Wignall and Roulet, 2013; Brealey et al., 2012; Demirguc-Kunt et al., 2013). Panel A of Table 4.1 provides a further overview of this type of studies. This evidence has been one of the key arguments behind the proposals on the introduction of the LR (ESRB, 2015).

[3]In line with the literature (e.g. Mariathasan and Merrouche, 2014; Le Lesle and Avramova, 2012), average Basel RWs are defined as the ratio between risk-weighted assets (RWA) and the size of bank balance sheet.

The second strand of research, summarized in Panel B of Table 4.1, examines the drivers and the information content of Basel risk weights (RW). Mariathasan and Merrouche (2014) show that the banks which qualify for the IRB approach, systematically decrease their RWs after the introduction of Basel II. This reduction cannot be fully explained by changes in the portfolio choices of banks or by the improvement in their risk management practices. By iteratively excluding the alternative explanations of the secular decline in the RWs of the IRB banks, Mariathasan and Merrouche (2014) explain the phenomenon as being consistent with strategic manipulation aimed at reducing banks' required regulatory capital charges.

The incentive-based explanation of the decline in the RWs is also consistent with the evidence in Behn et al. (2014). The authors use loan-level data from German banks to examine their risk modeling choices around the introduction of Basel II. By exploiting within-borrower variation in the risk modeling approach - loans to the same borrower may be subject to the IRB or the standardized credit modeling approach (SA), depending on the timing of the regulatory approval - Behn et al. (2014) show that banks report lower probabilities of default (PDs) and charge higher interest rates in the pool of the IRB loans than in the borrower-matched pool of the SA loans. When comparing the aggregate ex-post performance of the IRB and the SA loans, Behn et al. (2014) show that the IRB loans exhibit higher rates of default than the SA loans despite the former having been assigned lower RWs on average.

Finally, studies like Le Lesle and Avramova (2012) document substantial within and across-country variability in RWs and argue that it stems from a variety of sources, including banks' business models, risk profiles, and credit calculation methodologies. Importantly, it also reflects substantial variations in supervisory practices. Taken as a whole, the evidence suggests that heterogeneity in IRB practices across banks within and across countries may be another driver of poor explanatory performance of RWs.

Our results contribute to the above literature in several ways. In contrast to other studies that document informational superiority of simple capital measures, we show the under-performance of the RWCR in relation to the LR is not uniform across banks. Rather, we find that the underperformance of the RWCR is only pronounced in the IRB sample of banks, which - in line with the RWA literature (Table 4.1, Panel B) - are the ones most likely to strategically report their regulatory capital. In the non-IRB sample of banks, we find that the information contained in RWs is complementary to the information in a simple LR. Our results are also in line with Das and Sy (2012), who show that RWs display poorer performance in explaining future stock returns in the sample of the IRB banks than for the non-IRB banks. Similarly, we show that RWs fail to explain distress of the IRB banks, while they do have significant information content with respect to explaining distress of the non-IRB banks.

The second key contribution of this chapter is in its examination of the drivers of poor predictive performance of RWs in the IRB banks. Specifically, we propose a novel empirical test, based on the theoretical framework of Colliard (2014), which attempts to identify strategic reporting of banks by examining the link between negative capital shocks and the RW responses by banks.

We also contribute to the literature by proposing a new rule of thumb, based on bank size, to distinguish between the IRB and non-IRB banks. By exploiting the novel source of information on the capital calculation approach of banks covered in the *SNL Financial* database, we show that the sample size split at US$ 10 billion serves a good discriminatory feature to distinguish between banks that follow the IRB or standardized approach (SA) in calculating their regulatory capital. Specifically, banks larger than $10 billion predominantly apply the IRB approach, whereas the ones below the threshold in majority opt for the SA approach.

Finally, we complement the literature by finding some support for the claim that bank intangibles served as relatively poor loss absorbers during the recent crisis. Specifically, we find that DTAs have the strongest positive association with bank distress for large banks in Europe, but are otherwise a relatively insignificant predictor of bank distress in other samples. Goodwill, on the other hand, exhibits a strong positive association with bank distress for the non-IRB banks in the U.S.

The plan of the chapter is as follows. Section 4.2 provides an additional context behind Basel III capital regulations and develops the main hypotheses. Section 4.3.1 describes the data and methodology, followed by Section 4.4, which discusses the main empirical results. Section 4.5 discusses the key results and concludes.

Table 4.1 – Literature on the effectiveness of risk sensitive and risk-insensitive capital measures

Paper	Key Findings
Panel A: Performance comparison between risk-sensitive and risk-insensitive capital measures	
Aikman et al. (2014)	Simple risk-insensitive approaches of calculating bank capital often outperform more complex risk-sensitive approaches in terms of predicting bank distress.
Berger and Bouwman (2013)	Higher pre-crisis capital level associated with higher probability of survival for small banks at all times. For medium to large banks, the relation between capital and probability of distress holds only during the crisis. Large banks defined as banks with assets in excess of $3 billion. Risk-sensitive (Basel I) capital measures display lower association with bank distress than balance-sheet based leverage ratio.
Blundell-Wignall and Roulet (2013)	Basel Tier 1 ratio underperforms un-weighted leverage ratio in explaining bank distance-to-default.
Brealey et al. (2012)	Book leverage ratios out-perform Basel capital ratios in predicting bank stock price performance. Banks with low RWs found to operate with higher leverage and more aggressive funding strategies.
Demirguc-Kunt et al. (2013)	Simple leverage ratio outperforms Basel-based leverage ratio in predicting bank stock performance during the GFC. The pattern is especially pronounced for large banks.
Haldane and Madouros (2012)	Simple measures of capital, such as the unweighted leverage ratio, outperform more complex risk-weighted measures in predicting failures of the US banks.
Mayes and Stremmel (2012)	Simple leverage ratio marginally out-performs risk-weighted capital ratio in predicting distress in the US sample of banks.
Panel B: Information content of Basel risk weights	
Behn et al. (2014)	Using natural experiment design and loan-level data, the paper shows that complex, model-based bank capital regulation fails to achieve the objective of linking capital charges to the actual asset risk.
Le Lesle and Avramova (2012)	The paper documents substantial cross-country variation in RWAs. The main drivers of the variation include different supervisory practices, banks' business models, and their risk profiles.
Mariathasan and Merrouche (2014)	Banks' reported risk weights decrease after the implementation of IRB approach. Decline in RWs is particularly pronounced for weakly capitalized banks and cannot be explained by improved risk-management. Authors argue that the decline is consistent with banks' strategic risk modelling.
Das and Sy (2012)	Banks with lower RWA perform better during the US and European crises. Performance is measured by stock returns and market measures of risk. The relationship between RWA and performance is weaker in Europe, where more banks follow the Basel IRB approach. RWA also less significant predictor of performance for larger banks.

[a] The table reports the key papers and findings in the literature on the bank distress prediction.

4.2 Hypotheses on Basel III Capital Regulation

This section develops a consistent set of hypotheses with respect to the Basel III regulations concerning the risk weighted capital ratio (RWCR), as summarized in Figure 4.1. Box 1 provides a definition of the regulatory capital ratio and its components. In sum, the RWCR consists of Core Equity Tier 1 Capital (CET1) in its numerator and risk-weighted assets (RWA) in the denominator. Conceptually, RWAs are a function of riskiness of exposures in bank balance sheet; for a given nominal unit of exposure, high-risk exposures are intended to command higher RWAs than low-risk exposures. Since the introduction of Basel II, capital regulation distinguishes between two broad ways of calculating RWAs. The first is a standardized approach (SA), which assigns risk weights according to the pre-defined templates, in which specific exposure categories are mapped to the corresponding risk weights. The second method is an internal rating-based (IRB) approach, in which a bank determines risk weights according to its internally developed risk models, subject to the approval by a regulator.

Some of the key changes in Basel III capital regulation, vis-a-vis the Basel II, involve[4]: (1) increasing the quantity of required capital, (2) improving the quality of regulatory capital, and (3) introducing the minimum LR as a backstop measure, which, in effect, decreasing the risk-sensitivity of capital requirements. Figure 4.1 summarizes how each of these developments affects the RWCR. It shows that the increases in quantity and quality of capital operate by improving the numerator, whereas the decrease in risk-sensitivity acts via the denominator.

In what follows, we discuss the main motivations behind these changes and develop empirical hypotheses underlying these motivations. Table 4.2 summarizes the hypotheses developed in this section.

[4]Table 4.9 in the Appendix outlines the implementation plans for various Basel III regulations since their initial publication (BCBS, 2010).

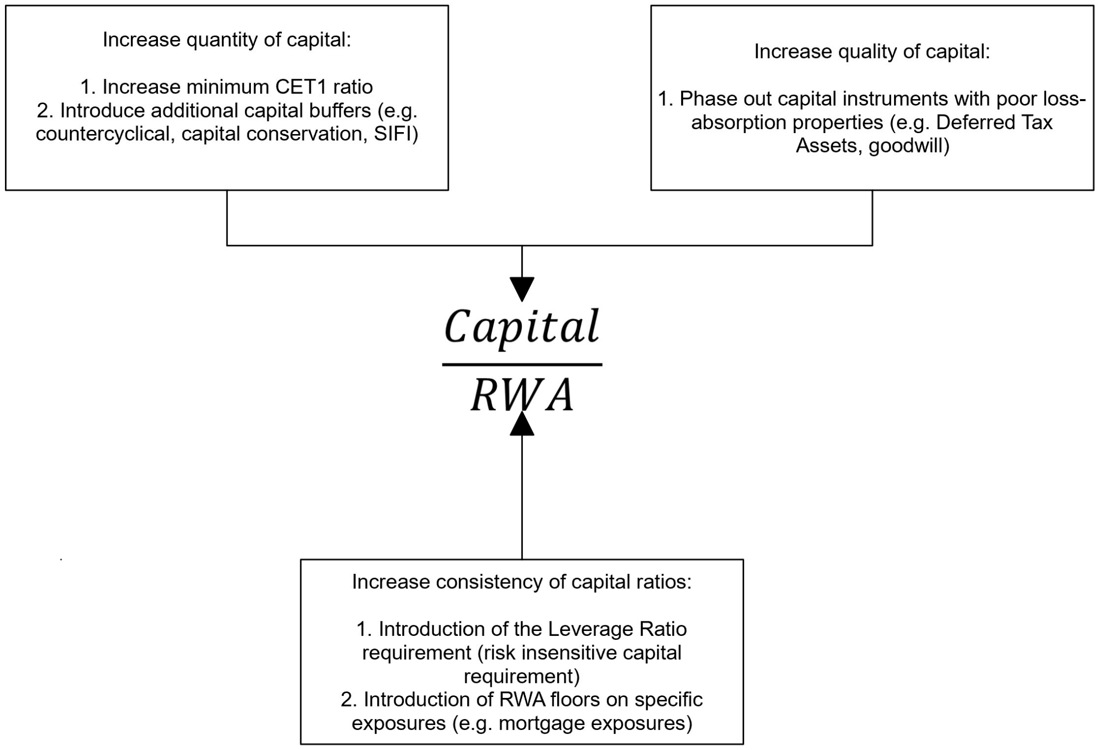


Figure 4.1 – How does Basel III regulation affect the regulatory capital ratio? The figure provides a summary of Basel III agreements with respect to various components of the regulatory capital ratio. Basel III regulation affects the capital ratio numerator by increasing the quantity of the required capital (e.g. via the introduction of additional buffers) as well as by improving its quality (e.g. by phasing out intangibles, such as DTAs and goodwill). With respect to the denominator, Basel III attempts to lessen the risk-sensitivity of RWA by introducing the risk-insensitive Leverage Ratio as a backstop measure. The so-called Basel III.5, which is an extension of the Basel III agreements, goes a step forward towards reducing risk-sensitivity of RWA by proposing minimum floors on specific exposures.

Box 4.1

Dissecting the Risk-Weighted Capital Ratio

The principal difference between risk-sensitive and risk-insensitive capital measures is their denominator. In the case of the former, bank capital is scaled by a risk-insensitive exposure measure, typically book assets augmented by the bank's off-balance sheet exposures. In the case of the latter, the denominator consists of the banks' RWA, determined by the bank's internal risk models for banks which follow the IRB approach, or pre-defined risk-based capital charges for banks that follow the standardized approach:

$$\begin{aligned} \text{Leverage Ratio (LR)} &= \frac{\text{Capital}}{\text{Risk-insensitive exposure}} \\ \text{Risk-Weighted Capital Ratio (RWCR)} &= \frac{\text{Capital}}{\text{RWA}}. \end{aligned} \tag{4.1}$$

In what follows, we use banks' total book assets as the risk-insensitive exposure measure in the above formula. With this, the relationship between the two measures can be succinctly summarized as follows:

$$\begin{aligned} \text{RWCR} &= \frac{\text{LR}}{\text{RW}}, \text{ where:} \\ \text{Basel Risk Weights (RW)} &= \frac{\text{RWA}}{\text{TA}}. \end{aligned} \tag{4.2}$$

Basel III Aim 1 ***Increase the quantity of bank capital.***

One of the most visible changes in Basel III concerns the increase in the required quantity of bank capital. This is motivated by the argument that bank equity serves as the primary absorber of losses in the course of banking operations. As such, it represents the first line of defense against insolvency in case of a deteriorating financial situation. Once its equity capital is significantly depleted, a bank becomes insolvent, which necessitates some form of bank restructuring, either with or without revoking a bank charter. During the GFC, many banks - especially in the advanced economies - experienced unprecedented levels of losses that rapidly eroded bank capital buffers, which, in turn, precipitated widespread financial distress in the banking sector. Increases in the minimum capital buffers promoted in Basel III are aimed at increasing the resilience of banks to unanticipated future shocks.

Theoretically, bank capital is expected to correlate negatively with the probability of distress. This is assumed to hold both mechanically - the higher the buffer, the more lossess the bank can accumulate before it fails - as well as via improved incentives that higher capital provides to bank managers (Holmstrom and Tirole, 1997). The incentive channel may operate via improving the bank's incentives to monitor its borrowers or by reducing asset-substitution moral hazard (Freixas and Rochet, 2008). This line of argument is condensed in the following hypothesis:

Hypothesis 1.1 ***Negative association between bank capital and the probability of distress.*** *To the extent that capital disclosed in a bank's financial accounts* *captures the bank's loss-absorbing capacity, it is expected to display a negative association with the probability of distress.*

Basel III Aim 2 ***Move towards less risk-sensitive capital regulation.***

Apart from increasing the quantity of the required bank capital, Basel III also marks the move towards less risk sensitive capital requirements. One of the key developments in this area is the introduction of the minimum leverage ratio (LR). It has been motivated by at least three sets of arguments (see ESRB, 2016; Grill et al., 2016; ESRB, 2015):

- **Risk-sensitive capital measures may be noisy and subject to model risk and manipulation.** With the adoption of Basel II regulation in the mid-2000s, especially the large banks qualified to use the internal credit risk models (so called internal rating-based approach - IRB) in determining capital charges for their counter-party exposures. Discretion granted by the IRB approaches has been motivated by the belief that more flexibility in risk measurement allows for more nuanced representation of risks in bank balance sheets. Computation of risk-sensitive capital requirements - especially in the banks that follow the IRB approach - relies on banks' internal modeling of the PD and the loss-given-default (LGD) distributions in their portfolios. Insofar as the models fail to capture the underlying risks in bank portfolios, and do so systematically, there is a concern that the resulting capital requirement may be insufficient to cover the risks[5].

  One can distinguish between two sets of arguments on why RWCR may be of lower information value than risk-insensitive measures of capital. The first attributes informational inferiority of RWCR to 'honest' mistakes on the part of banks, which try but fail to capture the underlying risks in their portfolio. To start, there is the uncertainty with respect to the parameters guiding the portfolio loss distribution, assuming the DGP[6] as a given ('known-unknowns'). Banks may fail to produce the correct estimates of DGP parameters due to short historical samples, cyclicality of model inputs, or due to constraints induced by the accounting standards (e.g. with respect to the recognition of

[5]Many market participants have voiced concern that the usage of internal models coupled with the lack of disclosure about bank IRB methodologies has significantly impaired the information value of the reported risk and capital metrics. For more discussion on this issue see BCBS (2013) and Le Lesle and Avramova (2012).

[6]Acronym for Data-Generating Process.

losses). In addition, there can be uncertainty in the structure of the underlying DGP itself ('unknown-unknowns', model uncertainty). According to this view, bank internal models may fail to capture latent risk factors, which, when they materialize, may produce significant losses to the bank. Consistent with this view, Borio and Drehmann (2009) show that bank risk estimates, as captured by RWs, are pro-cyclical in a sense that they provide the lowest risk estimates at the peak of a credit cycle, when the actual financial stability risks are the highest. They call this a paradox of instability: "the financial system can appear strongest precisely when it is most fragile" (Borio and Drehmann, 2009).

The second line of argument explains informational inferiority of risk-sensitive measures as a consequence of strategic reporting by banks. This type of explanation typically assumes that a bank supervisor has imperfect information about the true quality of a bank and must rely on the bank's internally produced disclosure. This friction gives a bank the ability to mis-report its financial condition. Under some circumstances, the bank has an incentive to exploit discretion and reporting opacity by under-reporting its risks, and thus boosting its reported risk-weighted capital. Papers like Blum (2008), Colliard (2014), and Behn et al. (2014) show that this incentive increases with (1) the proximity of bank capital to the minimum regulatory threshold, (2) the degree of financial distress experienced by the bank, (3) the complexity and opacity of the risk-measurement model, (4) intrusiveness of the supervisory oversight, and (5) the degree of sensitivity of the capital requirements to the reported measured risks (see Behn et al. 2014; Colliard 2014).

- **In terms of measuring bank risk and performance, simple risk-insensitive measures of bank capital empirically outperform risk-weighted capital measures.** Studies like Aikman et al. (2014), Berger and Bouwman (2013), Haldane and Madouros (2012), and Mayes and Stremmel (2012) find that risk-insensitive capital measures often out-perform risk-sensitive measures in predicting bank default. Risk insensitive capital measures also appear to be better predictors of future bank stock market performance (Blundell-Wignall and Roulet, 2013; Brealey et al., 2012; Demirguc-Kunt et al., 2013). This evidence has been one of the key arguments behind the proposals on the introduction of the macroprudential LR (ESRB, 2015).

- **Risk-insensitive capital requirements serve as a backstop against excessive leverage.** The minimum LR capital requirement imposes an upper

> limit on bank balance sheet size. Within the risk-weighted framework, banks could increase their balance sheet exposures while keeping their capital ratio constant by: investing in assets with low regulatory risk weights, or by optimizing their internal models in a way that generated the lowest capital requirement for a given level of exposures.

It is worth noting that the introduction of the LR is orthogonal to the risk-sensitive philosophy of Basel II. Conceptually, risk-sensitive capital requirements - the key focal area of Basel II - were intended to provide a superior measure of bank resilience, by the virtue of the fact that they take into the account the risk of bank investments. To see this point, consider a hypothetical situation with two banks, whose total exposure and capital are nominally the same, with bank A investing its entire exposure in a safe asset (e.g. government bonds) and bank B investing in a risky asset (e.g. corporate loans). Also assume that the risk of bank investments is positively related to its risk weights (i.e. a number of units of RWA that bank reports for each unit of risk-insensitive exposure). From the set-up it follows that the LR of the two banks would be the same while the RWCR of bank B would be lower from the RWCR of bank A. Arguably, bank A is less likely to experience financial distress, and should thus be considered as relatively more resilient than bank B. At the first blush, the growing empirical evidence (Table 4.1, Panel A) on the superior performance of the LR relative to the RWCR is thus a conundrum. However, as noted above, it may be explained by banks using inaccurate models - either inadvertently or strategically.

Based on the above discussion, we formulate the following hypothesis:

Hypothesis 2.1 ***Risk-sensitive measures are informationally inferior to risk-insensitive measures of bank capital.*** *To the extent that risk-sensitive measures of bank capitalization (such as the RWCR) suffer from mis-measurement and manipulation, they are expected to be less informative about the prospects of bank distress than the risk insensitive measures, such as the leverage ratio (LR).*

Box 4.1 shows that by dividing both the numerator and the denominator of the RWCR by bank balance sheet size (i.e. a risk-insensitive exposure measure), the RWCR can be expressed as the LR, scaled by the average Basel RW. Realizing that the LR and RWCR only differ in the RW component, Hypothesis 2.1 can be re-expressed as follows:

Hypothesis 2.1.1 ***Informational inferiority of RWCR to LR will be reflected in statistically insignificant or negative association between RW and bank distress.*** *To the extent that the RWs do capture an additional default-relevant information, not already included in the risk-insensitive capital ratio, their conditional association with bank distress (i.e. conditional on the risk-insensitive capital ratio) is expected to be positive.*

While Hypotheses 2.1 and 2.1.1 in principle apply to all banks, they can be distilled further by noting that the degree of discretion is particularly significant for banks which follow an IRB approach to the calculation of credit risk in their portfolio. The incentive problem inherent in the IRB approach is epitomized in Andrew Haldane's (2013) quote at the beginning of the chapter: "Marking your own exams is a perilous pursuit." It implies the following hypothesis:

Hypothesis 2.2 ***The information content of risk-sensitive measures is expected to be lower in banks that follow the IRB approach.*** *If discretion hampers information value of bank disclosure, risk sensitive measures of bank capitalization are expected to be less informative with respect to predicting bank distress for banks that follow the IRB approach than for the ones that follow the standardized approach.*

Basel III Aim 3 ***Increase the quality of bank capital.***

The Basel III has imposed significant limitations on the instruments that qualify as capital for regulatory purposes. Underlying these changes is a concern that multiple instruments that banks have hitherto used to meet their capital requirements are thought to have only limited loss-absorption properties. There are two main sets of instruments that are facing restrictions under the new regulation: (a) DTA, and (b) goodwill and other intangibles.

- **Deferred Tax Assets.** DTAs are tax assets that banks generate from operating losses by virtue of the fact that in many countries tax authorities allow banks to offset incurred losses against their future profits (thus lowering their future tax liability). Basel II treated DTAs as CET1 capital, and following the widespread banking sector losses during the GFC, DTAs became a prominent source of capital for banks in many countries, especially in the Southern Europe. Basel III aims to limit reliance on DTAs due to two sets of concerns. First, materialization of DTAs is contingent on banks' return to profitability in the future, which may not be a viable outcome for severely distressed banks. Second, the sovereign debt crisis in Europe has generated significant fiscal strains in many countries, which opened the possibility that DTAs may not be honored in countries with the least fiscal space.

- **Goodwill and other intangibles.** Basel III also reduces the amount of goodwill and other intangibles that banks are allowed to count as capital. The reasoning behind their reduction is similar to the one behind DTAs, i.e. due to their poor loss-absorption qualities.

We condense the above discussion in the following hypothesis:

Hypothesis 3.1 ***The amount of DTAs and intangibles in banks' capital base is positively associated with the probability of distress, after controlling for banks' tangible equity.*** *If DTAs and intangibles indeed have poor loss absorption qualities, banks that rely on these components to meet their regulatory capital requirements are more likely to experience future distress.*

Table 4.2 – Hypotheses on Basel III

Aim	Hypothesis	Test
A-1: Increase quantity of bank capital	H-1.1: Negative association between bank capital and the probability of distress.	Table 4.6, Panel A
A-2: Move towards less risk-sensitive capital regulation.	H-2.1: Informational inferiority of risk-sensitive measures to risk-insensitive measures of bank capital.	Table 4.6, Panels A and B
	H-2.1.1 Informational inferiority of RWCR to LR will be reflected in statistically insignificant association between RW and bank distress.	Table 4.6, Panel C
	H-2.2 Information content of risk-sensitive measures is expected to be lower in banks that follow the IRB approach.	Table 4.6, Panel C
A-3: Increase the quality of bank capital.	H-3.1 Amount of DTAs and intangibles in banks' capital base is positively associated with the probability of distress, after controlling for banks' tangible equity.	Table 4.7

[a] The table summarizes the hypotheses developed in Section 4.2.

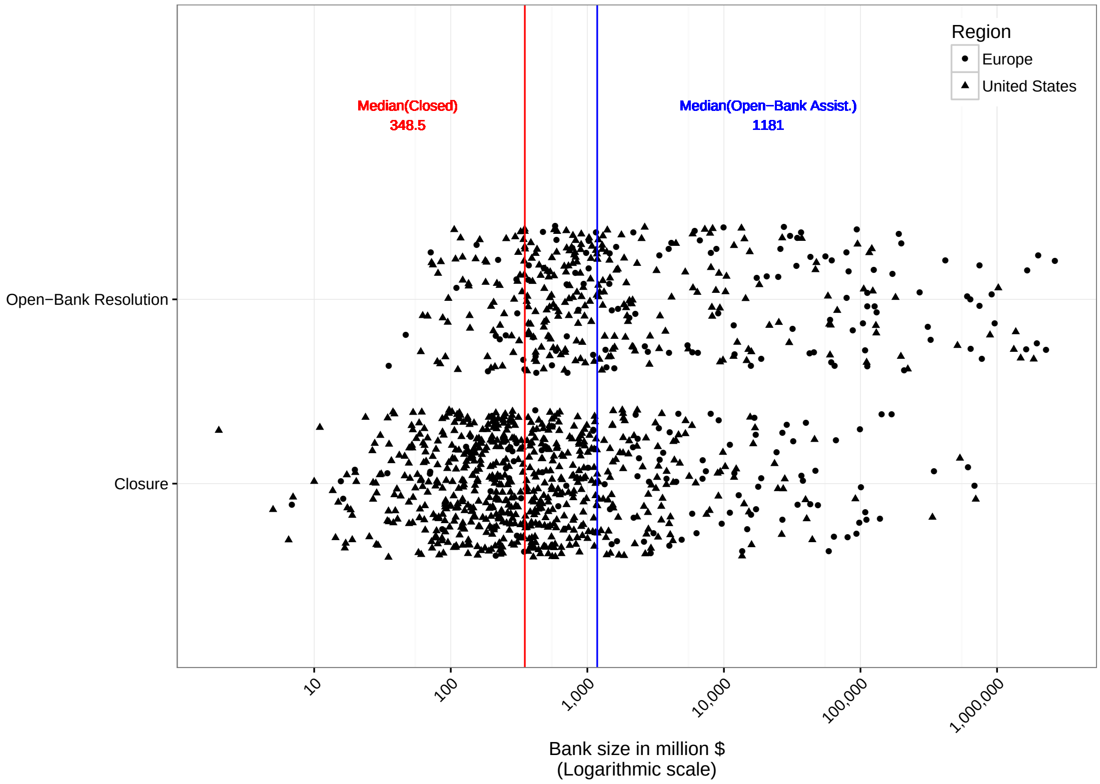


Figure 4.2 – The figure shows a jitter plot with bank asset size - reported in million US$ - on the horizontal axis and bank distress types on the vertical axis. Data on bank distress events come from Cizel and Rijken (2016). Bank balance sheet information is taken from *Bankscope*. Each unit in the plot corresponds to the 3-year pre-event average size of a bank that experiences one of the distress events. Dots correspond to the European and triangles to the U.S. banks.

4.3 Data and Methodology

4.3.1 Data

The analysis in this chapter focuses on banks residing in Western Europe and the United States.

Bank Distress Events

Our bank distress events come from the analysis in Chapter 3, where we construct a comprehensive database of bank distress events, drawing on a number of publicly available sources. The range of events covered by the database includes bank liquidations, bankruptcies, regulatory receiverships, distressed mergers, distressed dissolutions, and open-bank assistance, typically in the form of government recapitalization of

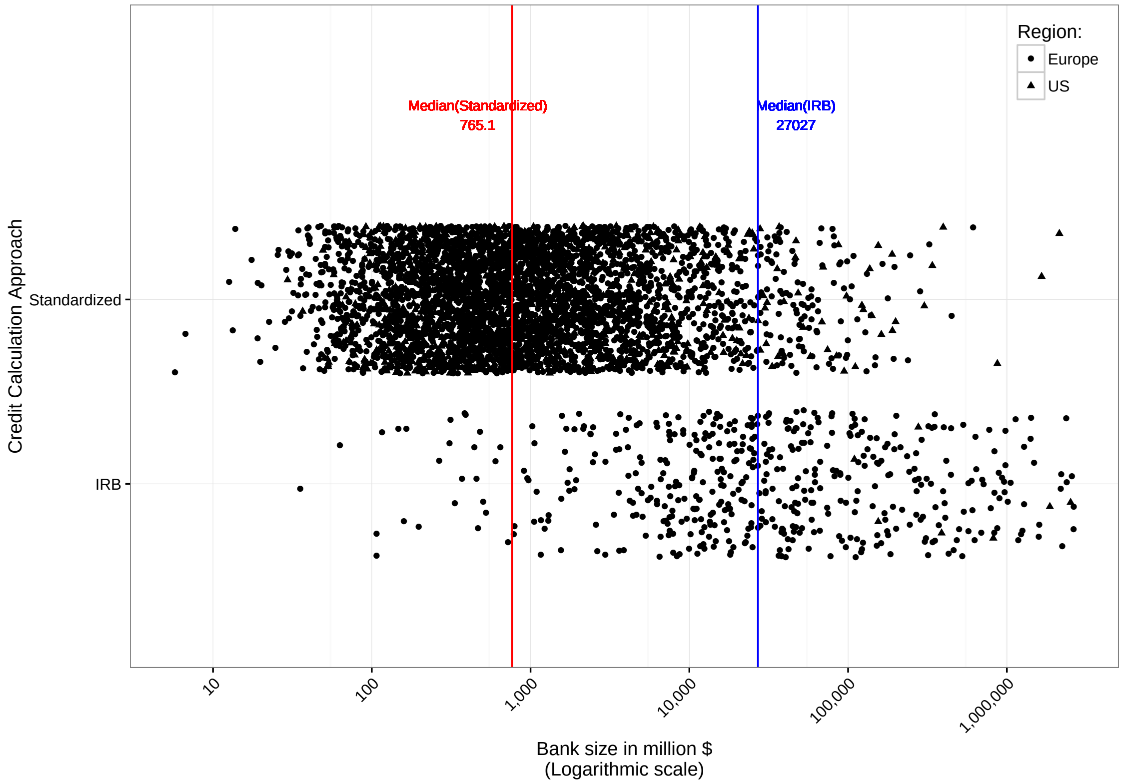


Figure 4.3 – The figure shows a jitter plot with bank asset size - reported in million US$ - on the horizontal axis and Basel credit calculation type, followed by a bank, on the vertical axis. Data on banks' Basel credit calculation approach and corresponding bank balance sheet sizes come from *SNL Financial* database. Each unit in the plot corresponds to the latest available 3-year average size of a bank that follows a particular credit calculation approach. Dots correspond to the European and triangles to the U.S. banks.

ailing banks. Events are categorized into two broad groups of bank resolution: (1) bank closures, corresponding to resolutions in which distressed banks cease to exist as independent entities, and (2) open-bank resolutions, in which banks are allowed to continue operating with the assistance of a government bailout. Using the database, we create a distressed bank indicator, which equals one if the bank experiences either bank closure or open-bank resolution τ-years in the future (see below). We manually match bank distress events with the balance sheet information from Bankscope (see below). For more information on the construction of the database see Chapter 3.

Figure 4.2 shows the distribution of balance sheet sizes for banks that are closed or resolved via an open-bank resolution. The figure indicates that distressed banks resolved via closure are typically smaller than the ones resolved via an open-bank resolution. Specifically, the median size is $348 million for banks that are closed and $1.2 billion for the ones that are resolved as going concerns. At least to some extent this is likely to be a manifestation of the "too-big-to-fail", where a failure of a large bank may involve significant externalities for the financial system, which, in turn, may motivate bank supervisors to keep the institution operating as a going concern.

Distinguishing Between the IRB and Non-IRB Banks

Some of the hypotheses in Section 4.2 differentiate between banks that do or do not follow the IRB approach to the calculation of their regulatory capital. We collect the information on banks' Basel credit calculation approach and on their respective balance sheet sizes from the *SNL Financial* database. Figure 4.3 shows the distribution of bank balance sheet sizes for the IRB and non-IRB banks. Banks which apply IRB tend to be significantly larger than their non-IRB peers. The median size is $27 billion for the IRB and $765 million for the non-IRB banks. Also note that a large majority of IRB banks (and only a small percentage of the non-IRB banks) has assets in excess of $10 billion. In the subsequent analysis we use this observation to distinguish between the two groups of banks.

The reason why we do not use the precise bank credit calculation information from the *SNL Financial* is that the subsequent analysis uses balance sheet information from *Bankscope*, which has a superior cross-sectional and time-series coverage relative to the *SNL*. While this could have been overcome by matching the *SNL* information with *Bankscope*, this unfortunately cannot be done directly, due to the lack of a common bank identifier across the two databases[7]. Based on this consideration, and given that the two sets of banks are relatively cleanly separated at the $10 billion balance sheet threshold, the subsequent analyses refer to the banks with assets in excess of $10 billion as the IRB sample, and to the rest as the non-IRB sample.

Bank Balance Sheets

We collect the bank financial information from Bankscope. We limit our analysis to the following types of banks: (1) bank holding companies, (2) commercial banks, (3) cooperative banks, (4) mortgage banks, and (5) savings banks. When a given bank reports accounts at different levels of consolidation, we only keep the reported figures at the highest level of consolidation. Unless otherwise stated, all accounting measures are scaled by the total book value of assets in the same fiscal period.

[7]Another possibility would be to match bank-level information in *Bankscope* and *SNL* manually. This, however, would be prohibitively expensive given that each of the two datasets contains several thousand entities.

Tables 4.3 and 4.4 provide a summary of bank balance sheet items used in the subsequent analysis for the large (IRB) and small (non-IRB) banks, respectively. For each variable we report a mean and standard deviation (in parentheses), separately for European and the U.S. banks. The final column in each table reports the difference between the European and for the U.S. banks and the result of a statistical test of the difference.

Several key observations can be drawn from Tables 4.3 and 4.4:

- CET1 capital of the large (small) banks on average comprises around 6.5% (11%) of total book assets and is on average higher in the U.S. than in Europe.

- Large (IRB) banks on average report lower RWs (58%) than do small banks (68%). While this is likely to reflect differences in the investment portfolio of the two types of banks, it is also consistent with the implicit incentives given by Basel II to banks that qualified for the IRB.

- Off-balance sheet assets, which are a part of the of the Basel III LR denominator, are on average larger for the large (16.9%) than for the small banks (10.9%). Off-balance sheet items are particularly sizable for the large U.S. banks, where they amount to 28% of balance sheet size.

- Intangibles, such as DTAs and goodwill are small for the small banks, where they amount to less than 4% of tangible bank equity in total. This is generally not the case for the large banks. Goodwill is especially important for the large U.S. banks, where it constitutes around 16% of tangible bank equity. DTAs are relatively more important in Europe, where they represent about 5% of banks' tangible capital.

4.3.2 Empirical Model

Methodologically, this chapter follows closely the set-up and framework of Chapter 3. Specifically, we test the hypotheses in Section 4.2 in the context of early-warning model (EWS) for banks. In essence, the exercise involves modeling of a binary response variable, which is bank distress at some future time horizon, via accounting based information available at time t. Specifically, let T_i denote the time at which bank i experiences distress and exits the sample. In line with the past research, we model probability that a bank becomes distressed within the time interval $[t+s, t+s+\Delta t]$,

Table 4.3 – Summary of the key banking measures for the non-IRB sample (bank assets below 10 billion USD).

	Non-IRB sample (size < \$10 billion)			
	Region			
	Europe	United States	All	Difference (EU - US)
Panel A: Controls				
Unreserved Impaired Loans (% of Equity)	27.1	5.3	7.2	21.8***
	(32.0)	(26.0)	(27.3)	(0.3)
Loan Loss Provisions (% of Gross Loans)	0.7	0.5	0.6	0.1***
	(1.0)	(1.1)	(1.1)	(<0.1)
Interest Expense (% of Interest Bearing Liabilities)	2.4	2.1	2.1	0.3***
	(1.3)	(1.1)	(1.1)	(<0.1)
Net Interest Margin	2.6	4.0	3.6	-1.4***
	(1.2)	(1.1)	(1.3)	(<0.1)
Non-Interest Expense (% of Gross Revenues)	69.0	74.0	72.7	-5.0***
	(20.3)	(26.7)	(25.3)	(0.2)
Panel B: Basel measures				
CET 1 (% of Total Assets)	10.3	11.2	11.1	-0.9***
	(6.9)	(7.6)	(7.5)	(0.1)
CET 2 (% of Total Assets)	3.2	0.8	1.1	2.3***
	(3.7)	(0.8)	(1.7)	(<0.1)
RWA (% of Total Assets)	69.6	68.4	68.5	1.2***
	(17.3)	(14.4)	(14.6)	(0.2)
Tier 1 Regulatory Capital Ratio (as reported)	15.9	18.0	17.8	-2.1***
	(12.1)	(17.1)	(16.7)	(0.2)
Off-Balance Sheet Assets (% of Total Assets)	8.3	11.8	10.9	-3.5***
	(13.4)	(15.3)	(14.9)	(0.1)
Goodwill (% of Equity)	0.4	3.2	2.5	-2.8***
	(2.7)	(7.9)	(7.1)	(0.1)
Deferred Tax Assets (% of Equity)	1.3	0.9	1.0	0.4***
	(3.6)	(3.1)	(3.3)	(<0.1)

Notes:
[a] The table reports summary statistics for the set of covariates used in the subsequent analysis. The IRB (non-IRB) banks are defined as the banks with the size of their balance sheets above (below) the \$10 billion threshold. See Section 4.3.1 for the additional details on the classification.

given the information at time t, as a linear combination of bank specific covariates x_{it}:

$$P(D\{T_i \in [t+s, t+s+\Delta t]\} \mid \mathcal{F}_t) = \text{Logit}(\alpha_{ic} + x'_{ict}\beta_t + \epsilon_{ict}) \tag{4.3}$$

where D is an indicator function that activates if a bank becomes distressed within $[t+s, t+s+\Delta t]$ time interval, and i, c, and t denote firm, country, and time indices, respectively. $\mathcal{F}_t$ denotes the information observable by an econometrician at time t, and β is a vector of coefficients. In the subsequent analysis β in Equation 4.3 is estimated via conditional fixed-effects logistic regression with bootstrapped standard errors to account for within-unit autocorrelation in residuals. When estimating models for different time periods, we remove observations of distressed banks that

Table 4.4 – Summary of the key banking measures for the IRB sample of banks (assets above 10 billion USD).

	IRB-banks (assets $\geq$ \$10 billion)			
	Region			
	Europe	United States	All	Difference (EU - US)
Panel A: Controls				
Unreserved Impaired Loans (% of Equity)	20.7	3.8	13.5	16.9***
	(32.9)	(23.2)	(30.3)	(1.0)
Loan Loss Provisions (% of Gross Loans)	0.6	1.0	0.7	-0.5***
	(0.9)	(1.5)	(1.2)	(<0.1)
Interest Expense (% of Interest Bearing Liabilities)	3.1	2.5	2.9	0.6***
	(1.6)	(1.7)	(1.7)	(<0.1)
Net Interest Margin	1.6	3.3	2.1	-1.7***
	(1.0)	(2.1)	(1.6)	(<0.1)
Non-Interest Expense (% of Gross Revenues)	60.6	58.8	60.0	1.8**
	(22.7)	(24.9)	(23.5)	(0.7)
Panel B: Basel measures				
CET 1 (% of Total Assets)	5.3	8.4	6.5	-3.1***
	(2.3)	(4.7)	(3.8)	(0.1)
CET 2 (% of Total Assets)	1.3	1.7	1.5	-0.4***
	(1.7)	(1.5)	(1.6)	(0.1)
RWA (% of Total Assets)	50.3	71.3	58.3	-21.0***
	(19.9)	(17.6)	(21.6)	(0.7)
Tier 1 Regulatory Capital Ratio (as reported)	10.6	13.1	11.6	-2.5***
	(4.7)	(12.5)	(8.8)	(0.3)
Off-Balance Sheet Assets (% of Total Assets)	11.6	28.1	16.9	-16.5***
	(14.6)	(34.6)	(24.3)	(0.7)
Goodwill (% of Equity)	4.4	15.9	8.1	-11.5***
	(9.1)	(14.8)	(12.5)	(0.3)
Deferred Tax Assets (% of Equity)	5.4	1.5	4.2	3.9***
	(6.9)	(4.2)	(6.4)	(0.2)

Notes:
[a] The table reports summary statistics for the set of covariates used in the subsequent analysis. The IRB (non-IRB) banks are defined as the banks with the size of their balance sheets above (below) the \$10 billion threshold. See Section 4.3.1 for the additional details on the classification.

take place in the period after $(t + s + \Delta t)$.

Our methodology - as is the case with most EWS methods - is silent on the issue of causality. In other words, estimates of β coefficients are only indicative of the association between a covariate and distress, but do not imply the causal relation between the two. That being said, it is important to note that the hypotheses developed in Section 4.2 make implications concerning the predictive content of the RWCR components with respect to bank distress (i.e. their information content), and are thus agnostic on the causal chains that produce the associations.

4.4 Results

In what follows, we report results for tests of hypotheses developed in Section 4.2 and summarized in Table 4.2. All tests are performed separately for the following groups: (1) bank closures and open-bank resolutions, (2) large and small banks, interpreted as the IRB and non-IRB banks, and (3) European and the U.S. banks. All explanatory variables are standardized to have a mean zero and a unit variance, so that the magnitude of the reported coefficient corresponds to the impact of one standard deviation increase in the explanatory variable on the log-odds ratio. Consequently, the absolute magnitude of the coefficient can be used in a judgment of the relative economic importance of different variables in the specification.

4.4.1 Benchmark model estimation

We begin by reporting logistic regression results for the benchmark model of bank distress (Table 4.5). Subsequent tests in this section keep the benchmark model constant[8] and add Basel-based measures to test the Hypotheses in Table 4.2. Bank capital is negatively associated with bank distress but the association is statistically significant only in some of the subsamples (the association between distress and bank capital is further discussed in the next section). The association between distress and bank asset impairment - measured by the unreserved impaired loans and loan loss provisions - is mostly positive (as expected) but statistically significant only in the sample of small (non-IRB) banks. Bank funding costs, measured by banks' interest expenses (% of interest-bearing liabilities), display the most consistent pattern across the samples: the association with distress is positive, suggesting that banks that experience distress pay significantly more for their funding prior to the distress event. Bank profitability, measured by the interest spread is statistically insignificant in most samples. Bank inefficiency - measured by non–interest expense as a percentage of gross revenues - is statistically significant and positively related to distress only in the sample of the U.S. small banks. We note that the R^2 is surprisingly large in the case of the U.S. bank closures. As already argued in Chapter 3 this may be due to the so-called "controlled-failure" process, whereby the regulator (FDIC) identifies the distressed bank some time prior the observed failure, and forces it to clean the balance sheets before the bank is dissolved.

[8]Constant in a sense that the selection of variables in the benchmark model does not change across specifications. The only exceptions are Panels A and C in Table 4.6, which substitutes the CET1 capital ratio in the benchmark specification by the alternative measures of bank capital.

Table 4.5 – Benchmark Model Estimation

	Dependent variable is distress within 1 year[a]							
	Non-IRB sample (size < 10BN)				IRB sample (size ≥ 10BN)			
	Bank Closure		Open bank resolution		Bank Closure		Open bank resolution	
	EU	US	EU	US	EU	US	EU	US
CET1 (% of Total Assets)	-6.04***	-4.48***	-0.20	-0.30	-3.16***	0.36*	-0.12	-0.51
	(0.92)	(0.26)	(0.68)	(0.21)	(1.09)	(0.22)	(1.07)	(0.53)
Unreserved Impaired Loans/ Equity	0.35**	0.35***	0.34	-0.48***	0.08	0.28	0.08	-1.05
	(0.14)	(0.03)	(0.24)	(0.17)	(0.16)	(0.20)	(0.17)	(0.68)
Loan Loss Provisions / Gross Loans	0.20	0.48***	0.33**	-0.12	0.03	0.32	0.10	-0.13
	(0.16)	(0.05)	(0.16)	(0.14)	(0.30)	(0.20)	(0.23)	(0.25)
Interest Expense / Interest-Bearing Liab.	0.54	0.93***	2.42***	0.21	0.68**	0.87*	0.07	0.94***
	(0.53)	(0.16)	(0.77)	(0.19)	(0.33)	(0.45)	(0.27)	(0.36)
Net Interest Margin	0.58	0.04	0.55	0.14	-0.00	-0.83*	-0.36	0.16
	(0.54)	(0.15)	(0.34)	(0.16)	(0.61)	(0.43)	(0.55)	(0.31)
Non-Interest Expense/ Gross Revenues	-0.27	0.20***	-0.24	0.25***	0.15	0.17	-0.15	-0.15
	(0.21)	(0.04)	(0.25)	(0.07)	(0.17)	(0.15)	(0.18)	(0.19)
Log(Assets)	-0.03	-0.08	0.35	0.70***	0.20	-0.12	0.65***	0.15
	(0.17)	(0.06)	(0.25)	(0.06)	(0.21)	(0.31)	(0.22)	(0.19)
Pseudo R2	0.29	0.48[c]	0.13	0.06	0.11	0.17	0.05	0.07
Number of events	41	499	21	209	44	21	53	45
Number of obs.	3910	42945	1475	18736	668	832	394	351

Notes:

[a] The table reports the estimation coefficients from the following specification:

$$P(D_{ict} = 1) = \text{Logit}(\alpha_{ic} + x'_{ict}\theta_t + \epsilon_{ict})$$

where D_{ict} is the indicator of a bank becoming distressed within 1 year from time t, and i, c, and t denote firm, country, and time indices, respectively.

[b] In Europe, distress events are defined as the first time a given bank in a sample experiences one of the following: (a) bankruptcy/liquidation, (b) equity injection by the state (including nationalization), or (c) bridge loan by the state. For the U.S. banks, the distress indicator is constructed from the FDIC Failed Bank List (`http://www.fdic.gov/bank/individual/failed/banklist.html`). The accounting information is from Bankscope. The analysis considers the bank distress events that took place in the period 2005-13. The models are estimated for the sample of banks with assets larger than 100 million USD, for the period between January 2005 and December 2012.

[c] The R^2 is surprisingly large in the case of the U.S. bank closures. As already argued in Chapter 3 this may be due to the so-called "controlled-failure" process, whereby the regulator (FDIC) identifies the distressed bank some time prior the observed failure, and forces it to clean the balance sheets before the bank enters into the receivership.

4.4.2 Association between bank capital and distress: Test of Hypothesis 1.1

Table 4.6 reports the logistic regression results on the association between bank distress and bank capital, measured by RWCR (Panel A), and LR (Panel B). The association is negative and statistically significant for bank closures in the sample of small (non-IRB) banks. In the IRB sample (large banks), the association between bank capital and distress is statistically insignificant, and occasionally of the wrong sign. The main exception are European bank closures in the sample of large (IRB) banks, where the association with bank distress is negative and statistically significant.

A lack of statistically significant negative correspondence between RWCR and distress in the case of large banks suggests that the regulatory capital is a relatively poor measure of health for these banks. As stated in Hypothesis 2.2, one possible explanation is that the large (IRB) banks mis-measure their underlying risks, either strategically, or due to applying the wrong risk models (see the discussion in Section 4.2). We further explore this hypothesis in the section below.

4.4.3 Risk-sensitive vs risk-insensitive capital measures: Tests of Hypotheses 2.1 and 2.2

Are risk-sensitive capital measures informationally inferior to the risk-insensitive measures when it comes to explaining bank distress? A direct comparison of the results in Table 4.6 for the RWCR (Panel A) and LR (Panel B) does not provide a conclusive answer. The answer is clearly affirmative in the case of European bank closures for the sample of small (non-IRB) banks, where LR performs better than RWCR both in terms of the magnitude of the estimated coefficient ($\beta_{LR} = -6.04$; $\beta_{RWCR} = -5.89$) and especially in terms of the explanatory power ($R^2_{LR} = 0.29$; $R^2_{RWCR} = 0.18$). In all other cases, comparison of the two panels does not distinctively favor any of the two measures.

Panel C of Table 4.6 tries to shed additional light on the question by decomposing RWCR into LR and RW, and testing their individual contribution in explaining bank distress. As explained in Section 4.2, the key difference between LR and RWCR are RWs, and as stated in Hypothesis 2.1.1, the additive value of the *risk-sensitive* approach will be captured by the association between distress and RW, conditional on the LR.

While the estimated β_{RW} is positive in all specifications, it is statistically sig-

Table 4.6 – Performance of risk-sensitive and risk-insensitive capital measures in explaining bank distress

	Dependent variable is distress within 1 year[a]							
	Non-IRB sample (size < 10BN)				IRB sample (size $\geq$ 10BN)			
	Bank Closure		Open bank resolution		Bank Closure		Open bank resolution	
	EU	US	EU	US	EU	US	EU	US
Panel A: Risk-Weighted Capital Ratio (Risk-Sensitive)								
CET1 / RWA	-5.89***	-7.44***	-1.89	-1.61***	-3.04*	0.50	-1.14	-0.34
	(1.37)	(0.52)	(1.44)	(0.41)	(1.57)	(0.40)	(1.55)	(0.51)
Pseudo R2	0.18	0.47	0.14	0.07	0.09	0.20	0.06	0.06
Number of Obs.	3897	42919	1476	18751	631	708	402	355
Effects	Country*Year							
Controls	Yes[b]							
Panel B: Leverage Ratio (Risk-Insensitive)								
CET1 / TA	-6.04***	-4.48***	-0.20	-0.30	-3.16***	0.36*	-0.12	-0.51
	(0.92)	(0.26)	(0.68)	(0.21)	(1.09)	(0.22)	(1.07)	(0.53)
Pseudo R2	0.29	0.48	0.13	0.06	0.11	0.17	0.05	0.07
Number of Obs.	3910	42945	1475	18736	668	832	394	351
Effects	Country*Year							
Controls	Yes[b]							
Panel C: Incremental Value of Basel Risk Weights								
CET1/TA	-6.44***	-4.65***	-1.08	-0.14	-4.06***	-0.08	-0.89	-0.23
	(1.20)	(0.28)	(0.85)	(0.21)	(1.50)	(1.30)	(1.48)	(0.81)
RW	0.24	0.39***	1.04**	0.64***	0.22	0.09	0.34	0.01
	(0.27)	(0.10)	(0.42)	(0.13)	(0.26)	(0.36)	(0.28)	(0.24)
Pseudo R2	0.34	0.49	0.19	0.07	0.11	0.11	0.06	0.09
Number of Obs.	2846	40705	1429	17435	613	562	370	273
Effects	Country*Year							
Controls	Yes[b]							
Panel D: Incremental Value of Off-Balance Sheet Items								
CET1/TA	-6.48***	-4.64***	-1.17	0.08	-4.00***	0.04	-1.01	-0.23
	(1.21)	(0.28)	(0.88)	(0.20)	(1.51)	(1.22)	(1.50)	(0.81)
RW	0.24	0.39***	1.12**	0.90***	0.22	0.24	0.36	-0.00
	(0.27)	(0.10)	(0.46)	(0.13)	(0.26)	(0.35)	(0.28)	(0.24)
Off-balance sheet	-0.17	-0.05	-0.75	-1.75***	-0.16	-0.89*	0.14	0.03
	(0.59)	(0.07)	(0.83)	(0.22)	(0.41)	(0.54)	(0.29)	(0.14)
Pseudo R2	0.34	0.49	0.19	0.13	0.11	0.17	0.06	0.09
Number of Obs.	2846	40705	1429	17435	613	562	370	273
Effects	Country*Year							
Controls	Yes[b]							

Notes:

[a] The table reports the estimation coefficients from the following specification:

$$P(D_{ict} = 1) = \text{Logit}(\alpha_{ic} + x'_{ict}\theta_t + \epsilon_{ict})$$

where D_{ict} is the indicator of a bank becoming distressed within 1 year from time t, and i, c, and t denote firm, country, and time indices, respectively.

[b] Control variables included in the above regressions are the following: unreserved impaired loans (% of equity), loan loss provisions (% of gross loans), interest expense (% of interest-bearing liabilities), net-interest margin, non-interest expense (% of revenues), logarithm of total book assets. All explanatory variables are standardized to have a mean of zero and standard deviation of one. Bootstrapped standard errors are reported in parentheses.

[c] In Europe, distress events are defined as the first time a given bank in a sample experiences one of the following: (a) bankruptcy/liquidation, (b) equity injection by the state (including nationalization), or (c) bridge loan by the state. For the U.S. banks, the distress indicator is constructed from the FDIC Failed Bank List (`http://www.fdic.gov/bank/individual/failed/banklist.html`). The accounting information is from Bankscope. The analysis considers the bank distress events that took place in the period 2005-13. The models are estimated for the sample of banks with assets larger than 100 million USD, for the period between January 2005 and December 2012.

Table 4.7 – Quality of bank capital and and its impact on bank distress

	Dependent variable is distress within 1 year[a]							
	Non-IRB sample (size $<$ 10BN)				IRB sample (size $\geq$ 10BN)			
	Bank Closure		Open bank resolution		Bank Closure		Open bank resolution	
	EU	US	EU	US	EU	US	EU	US
Goodwill (% of Equity)	-0.03	-0.02	0.56	0.23***	-0.24	0.14	0.29**	0.21
	(0.28)	(0.06)	(0.43)	(0.05)	(0.15)	(0.24)	(0.14)	(0.15)
Deferred Tax Assets (% of Equity)	0.47	-0.05	-0.16	-28.29	0.69***	0.17	0.02	6.97
	(0.29)	(0.07)	(0.79)	(93.74)	(0.25)	(0.67)	(0.24)	(82.38)
Pseudo R2	0.35	0.49	0.20	0.08	0.15	0.12	0.08	0.15
Number of Obs.	2846	40705	1429	17435	613	562	370	273
Effects	Country*Year							
Controls	Yes[b]							

Notes:
[a] The table reports the estimation coefficients from the following specification:

$$P(D_{ict} = 1) = \text{Logit}(\alpha_{ic} + x'_{ict}\theta_t + \epsilon_{ict})$$

where D_{ict} is the indicator of a bank becoming distressed within 1 year from time t, and i, c, and t denote firm, country, and time indices, respectively.
[b] Control variables included in the above regressions are the following: unreserved impaired loans (% of equity), loan loss provisions (% of gross loans), interest expense (% of interest-bearing liabilities), net-interest margin, non-interest expense (% of revenues), logarithm of total book assets. All explanatory variables are standardized to have a mean of zero and standard deviation of one. Bootstrapped standard errors are reported in parentheses.
[c] Each column corresponds to the vintage of the accounting information that is used to model the bank distress events. In Europe, distress events are defined as the first time a given bank in a sample experiences one of the following: (a) bankruptcy/liquidation, (b) equity injection by the state (including nationalization), or (c) bridge loan by the state. For the U.S. banks, the distress indicator is constructed from the FDIC Failed Bank List (http://www.fdic.gov/bank/individual/failed/banklist.html). The accounting information is from Bankscope. The analysis considers the bank distress events that took place in the period 2005-13. The models are estimated for the sample of banks with assets larger than 100 million USD, for the period between January 2005 and December 2012.

nificant only for the sample of small (non-IRB) banks. This is consistent with the Hypothesis 2.2, and provides some support to the view that either (1) the IRB models suffer from model risk which diminishes their ex-post association with distress or (2) that the IRB banks strategically apply discretion in ways that makes their regulatory disclosures less informative. At the very least, the results indicate that the stated aim of the Basel risk-sensitive IRB approach, which is to improve the correspondence between banks' reported capital and their underlying risks, is not supported by our evidence on bank distress. Our results are also in line with Das and Sy (2012), who show that RWs display poorer performance in explaining future stock returns in the sample of the IRB banks than for the non-IRB banks. Similarly, we show that RWs fail to explain distress of large (IRB) banks, while they do have significant information content with respect to explaining distress in the sample of small (non-IRB) banks.

While we cannot distinguish between the incentive-based or the model-risk-based explanation for the poor performance of RWs in the sample of large (IRB) banks, Box 4.2 aims to shed additional light on this issue by studying temporal behavior of the RWCR components.

Another possible explanation for the poor statistical association between RWs and bank distress in the sample of large (IRB) banks is also a relatively low number of distress events, which may adversely impact the power of our tests to detect the association. This is another motivation for the analysis in Box 4.2, in which the tests do not rely on the number of distress events, and thus do not suffer from disparity in statistical power across different size-based samples of banks.

The analysis so far assumed that the risk-insensitive exposure measure used in the construction of LR consists of total book assets. The important omission in this definition, relative to the LR measure proposed by Basel III, is that it does not account for the off-balance sheet items. Panel D of Table 4.6 tests for the incremental information value of off-balance sheet assets while controlling for LR and RW. The coefficient on the off-balance sheet assets is statistically indistinguishable from zero in most cases. In the case of open-bank assistance events in the sample of the small (non-IRB) U.S. banks, the coefficient is statistically significant, but has a counter-intuitive direction of association with distress.

4.4.4 The Role of Intangibles in Bank Capital: Test of Hypothesis 3.1

Table 4.7 reports results of the tests on the association between intangibles (DTAs and goodwill) in bank capital and bank distress. The results suggest no clear patterns across samples and event types. DTAs exhibit a statistically significant positive association with distress ($\beta_{DTA} = 0.69^{***}$) only in the case of bank closures for the large (IRB) banks in Europe. This concurs with the anecdotal evidence that sees widespread use of DTAs by large banks in some of the peripheral European countries as one of the key factors for their subsequent distress and a need for public recapitalizations.

Next, goodwill and other intangibles are positive and statistically significant in the case of open-bank assistance events in the small banks in the U.S. as well as for the large banks in Europe. In most other cases $\beta_{Goodwill}$ is positive but statistically insignificant.

Overall, while there is some evidence that intangibles, such as DTAs and goodwill, have poor loss-absorption properties, the evidence is not uniform across samples and event types.

Box 4.2

Sensitivity of Basel Risk Weights to Changes in Bank Capital

Section 4.4.3 presented the evidence that RWs are relatively uninformative about the prospects of distress in the sample of large (IRB) banks, while they do partially explain distress in the sample of small (non-IRB) banks. As discussed above, the literature provides two broad sets of explanations for this finding.

First, the IRB banks are larger and more complex than their non-IRB counterparts. This may increase their susceptibility to model risk - the possibility that the internal models may fail to capture the underlying risk factors or that they may measure these factors imprecisely. Borio and Drehmann (2009) and ESRB (2015) show that bank risk weights are pro-cyclical in a sense that they provide the lowest risk estimates at the peak of a credit cycle, when the actual financial stability risks are the highest. Borio and Drehmann (2009) refer to this as the paradox of instability: "the financial system can appear strongest precisely when it is most fragile". To the extent that the IRB banks are more exposed to model risk than the non-IRB banks, the reported RWs are expected to be less informative about the banks' ex-post manifestation of risk, captured by distress events. This, in turn, may explain the result in Section 4.4.3.

The second explanation pertains to bank incentives: the IRB banks have comparably more discretion in reporting their RWs than the non-IRB banks. To the extent that they apply discretion to attenuate the impact of losses on their regulatory capital ratio - as suggested by the theoretical framework of Colliard (2014) - this would explain the low association between RWs and the ex-post distress for the IRB banks, vis-a-vis to the non-IRB counterparts.

This box aims to shed additional light on the plausible drivers of the low information content of RWs in the IRB banks. It does so by examining the temporal behavior of the numerator and the denominator in the regulatory capital ratio.

As discussed in Box 1, the RWCR can be expressed in terms of the LR and RWs:

$$\mathrm{RWCR} = \frac{\mathrm{LR}}{\mathrm{RW}}. \tag{4.4}$$

The relative movements in the RWCR components determine the overall change in the reported regulatory capital ratio. Changes in the numerator - the LR - may be offset or compounded by the changes the denominator - the RW.

One of the key insights in Colliard (2014) is that the IRB banks may dampen adverse shocks to their regulatory capital - the numerator - by strategically lowering their RWs. This insight has the following empirical implications:

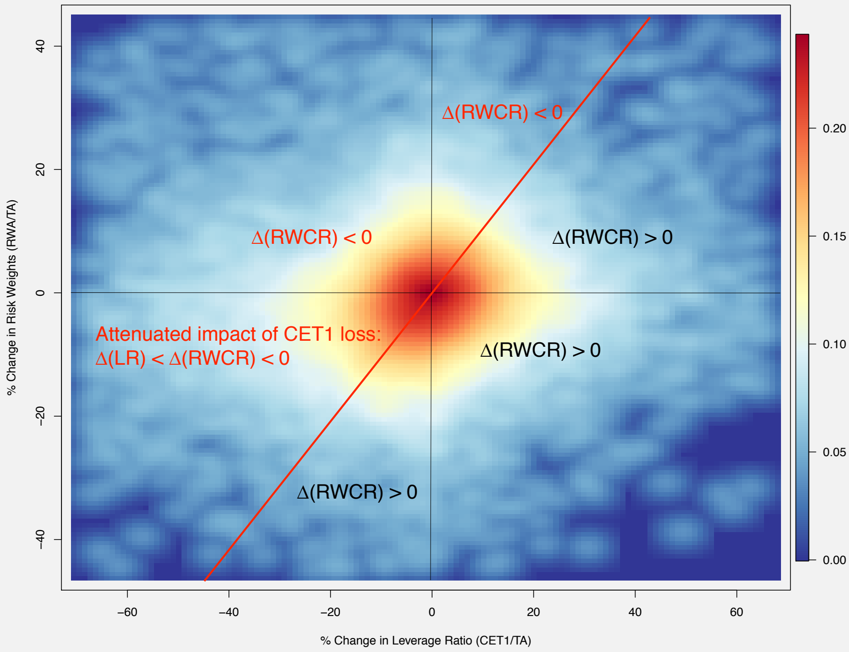
1. **Endogeneity of RW to LR.** For banks with discretion over the RWs, changes in the RW are expected to be partially driven by changes in the LR.

2. **Positive correlation between changes in RWs and changes in LRs.** The impact of the movement in LRs is expected to be matched by the parallel movements in the RWs, which, in turn, is expected to reduce the overall impact on the RWCR.

3. **Asymmetry in the RW-LR association across positive and negative LR changes.** In line with Colliard (2014), the incentive to dampen changes in the RWCR is the strongest in the case of the negative capital shocks. The positive co-movement between changes in RWs and LRs is thus expected to be the most pronounced in the case of the negative capital shocks ($\Delta LR < 0$).

We test the hypotheses using the *Bankscope* sample of banks from Section 4.4. We begin by computing the *year-to-year percentage changes* in LR and RW for each bank in the sample. Figure 4.4 shows a bivariate density contour plot of the resulting measures. The majority of the LR and RW year-to-year changes are concentrated in the range between -20% to 20%. The 45^o red line marks the LR-RW change combinations that result in a constant RWCR. All LR-RW combinations to the right of the line produce an increase in the reported RWCR, and all combinations on the left result in a decrease in RWCR. All combinations in the third quadrant above the red line result in an attenuated decrease in the RWCR (attenuated in a sense that $\Delta LR < \Delta RWCR < 0$). In line with the hypotheses discussed above, the majority of the observed LR-RW combinations from the IRB bank are expected to be concentrated in the third quadrant.

Figure 4.4 – The figure shows a bivariate density plot of percentage changes in LR and RWCR.



We examine the association between LR and RW changes by fitting a locally-weighted least squares regression (LOESS) to the observed LR-RW combinations in Figure 4.4. We fit the curve separately for each of the following size-based samples:

1. Bank size $<$ \$100 million (non-IRB banks).
2. Bank size $<$ \$10 billion (non-IRB banks).
3. Bank size $>$ \$10 billion (IRB banks).
4. Bank size $>$ \$100 billion (IRB banks).

Figure 4.5 shows the resulting LOESS fitted curves for each sample. One of the key observations in the figure is that the association between LR and RW changes increases with bank size. For small (non-IRB) banks, the RW changes are mostly independent from the changes in LR. For large (IRB) banks the association is strongly positive.

The evidence in Figure 4.5 - while preliminary - is consistent both with the incentive-based as well as the model-risk-based interpretations. Both theories anticipate differentials in the sensitivity of RWs across the IRB and non-IRB banks, the former because of the differing incentives and the latter because of higher model risk susceptibility of the IRB banks.

The key discriminating prediction of the incentive-based explanation is that sensitivity of RW changes to capital shocks depends on the direction of the capital shock: the incentive to adjust RWs downwards is the highest in the case of negative capital shocks, because the reduction would mitigate the erosion of the RWCR.

In order to test for the asymmetry in the RW sensitivity across positive and negative capital shocks we proceed as follows. We begin by estimating the elasticity of RW with respect to LR, which we define as:

$$E_{RW,LR} = \frac{\frac{\Delta RW_t}{RW_{t-1}}}{\frac{\Delta LR_t}{LR_{t-1}}}. \tag{4.5}$$

We estimate the $E_{RW,LR}$ for each sample of banks by estimating the following specification[a]:

$$\frac{\Delta RW_t}{RW_{t-1}} = \alpha + \beta \frac{\Delta LR_t}{LR_{t-1}} + \epsilon. \tag{4.7}$$

Note that $E_{RW,LR} = \hat{\beta}$. To test for the asymmetry in the elasticities across the positive and negative LR changes, we estimate the specification separately for the cases of negative capital shocks ($\Delta LR_{it} < 0$) and positive capital shocks ($\Delta LR_{it} > 0$).

Table 4.8 reports the results of the exercise. The magnitude of the estimated elasticities is consistent with the findings in Figure 4.5. The elasticities are large and statistically significant in the case of the IRB banks. For example, in the case of banks with assets in excess of $100 billion, each percentage-point (pp) fall in capital is associated with 0.3pp fall RWs. As a result, the RWCR falls by, on average, 0.7pp ($100 * (1 - \frac{0.99}{0.997}) = 0.7$). The movement in RWs thus attenuates the effect of a capital shock on the IRB bank's RWCR by 0.3pp for each 1pp fall in LR.

In the non-IRB sample, the elasticities are statistically significant but economically small. For example, in the case of banks with assets smaller than $10 billion, each 1pp fall in capital is associated with 0.034pp fall RWs (i.e.

the size of the elasticity is almost ten times smaller than in the IRB sample). As a result, the RWCR falls by, on average, 0.94pp ($100 * (1 - \frac{0.99}{0.9996}) = 0.94$). The movement in RWs thus have only a minor attenuation effect in the sample of the non-IRB banks.

The association between the changes in LR and RW is the strongest for the IRB banks also when judged by the regression R^2. In the IRB sample, variation in the LR changes explains about 8% of variation in the RW changes. In contrast, in the non-IRB sample the LR changes explains only 0.2% of the variation in RW changes.

The last column in Table 4.8 reports the results of the tests on the difference between the elasticities estimated in the sample of the negative capital shocks ($\Delta LR < 0$) and the positive capital shocks ($\Delta LR > 0$). The difference in RW elasticities - ($\hat{\beta}_{\Delta LR<0} - \hat{\beta}_{\Delta LR>0}$) - is positive and statistically significant in the sample of IRB banks. The evidence is consistent with the incentive-based explanation of the RW fluctuations (Colliard, 2014), which anticipates stronger positive association between LR and RW changes in the case of the negative capital shocks.

In the sample of the non-IRB banks, the elasticity differential is negative and significant only in the case of the banks with assets below $100 million.

Conclusion

The evidence from the analysis of the co-movement between the LR and RW changes is consistent with the incentive-based explanation of the RWs (Colliard, 2014). Around the negative capital shocks, RWs of large (IRB) banks tend to fall, which mitigates the effect of the shock on the RWCR. For the positive capital shocks, where the incentive to strategically report RWs is small, the association between the RW and LR changes is reduced. In the case of small (non-IRB) banks, which have less discretion in reporting their RWs, the variation in LRs explains only a small fraction of the variation in RWs. Overall, this evidence may explain why RWs are a relatively uninformative measure of banks' ex-post financial condition in the case of large (IRB) banks.

Figure 4.5 – Association between RW and LR changes across bank size group.

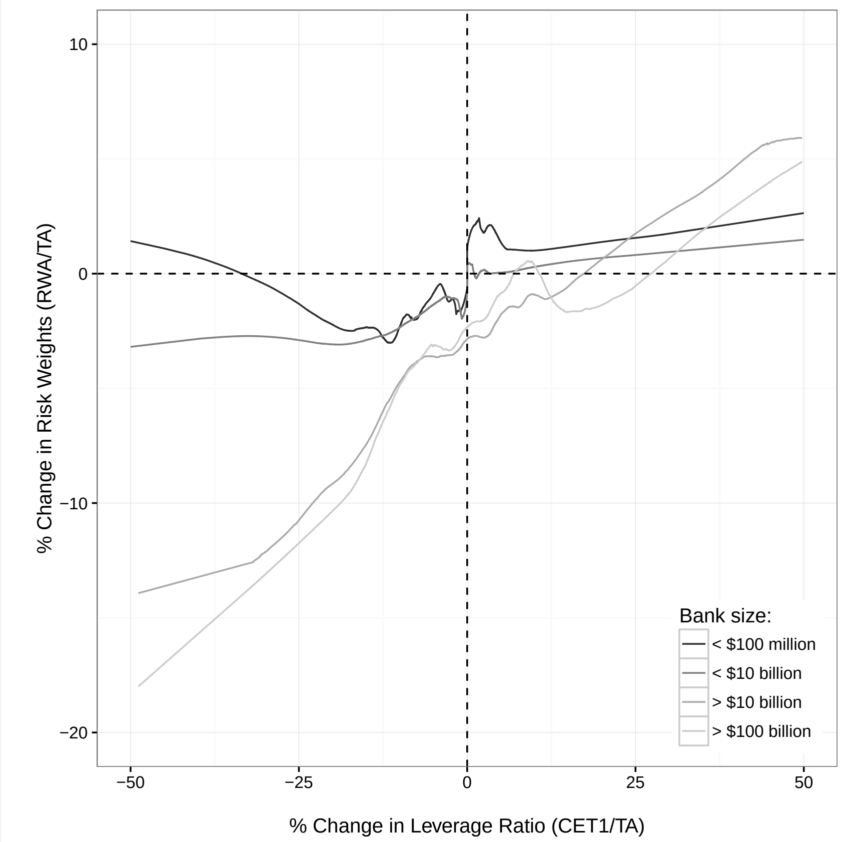


Table 4.8 – Estimation of the elasticities of RWs with respect to LR

Size	Direction of CET1 change						Difference	
	ΔCET1 < 0			ΔCET1 > 0				
	α	β	R^2	α	β	R^2	$Diff(\alpha)$	$Diff(\beta)$
< \$100 million	-1.702***	-0.035***	0.001	0.890***	0.017	0.001	-2.592***	-0.052***
	(0.172)	(0.010)		(0.218)	(0.014)		(0.042)	(0.017)
< \$10 billion	-1.525***	0.034***	0.002	-0.023	0.036***	0.002	-1.548***	-0.020
	(0.088)	(0.005)		(0.091)	(0.007)		(0.127)	(0.009)
> \$10 billion	-2.562***	0.319***	0.084	-3.282***	0.206***	0.062	0.720	0.113***
	(0.633)	(0.042)		(0.561)	(0.028)		(0.846)	(0.028)
> \$100 billion	-2.392*	0.332***	0.067	-2.358**	0.125**	0.030	-0.034	0.207**
	(1.323)	(0.087)		(0.901)	(0.042)		(1.601)	(0.097)

[a]The alternative way to estimate the $E_{RW,LR}$ is to estimate the following specification:

$$log(RW_t) = \alpha + \beta log(LR_t) + \epsilon. \tag{4.6}$$

As before, $E_{RW,LR} = \hat{\beta}$. This method results in the similar $E_{RW,LR}$ estimates as reported above.

4.5 Discussion and Conclusions

This chapter empirically examines three sets of core assumptions that are implicit in the new Basel III capital regulations: (1) distress-relevance of bank regulatory capital, (2) back-stop role of the risk-insensitive regulatory capital measures, and (3) poor loss-absorption properties of intangibles, such as DTAs and goodwill. Since each of these assumptions has empirical implications regarding the predictability of bank distress, the EWS framework for banks developed in Chapter 3 lends itself as a particularly suitable setting to test their validity.

Bank capital regulation in the form of Pillar 1 capital requirements constitutes a core tenet of Basel. It is predicated on the idea that bank capital represents the core measure of bank health because it is the only instrument that can absorb losses without triggering bank default. The key question for the regulators and investors is this, however: to what extent does regulatory capital reported by banks proxy the true economic capital in their balance sheets? Or put differently, to what extent do reported RWCRs posses the key property of the economic capital, which is to absorb losses?

We address this question by examining the historical association between bank distress and various types of capital ratios, including the RWCR and LR. To the extent that capital ratios reported by banks capture their economic capital, we expect to observe a strong negative association with bank distress.[9] We find a mixed evidence, however: while RWCRs serve as a good predictor of bank distress in the sample of small (non-IRB) banks[10], particularly in the case of U.S. bank closures, the association is statistically insignificant and occasionally of the wrong sign for the large (IRB) banks.

Basel III does recognize the incongruence between banks' reported regulatory capital and their economic capital, and tries to address it with two broad sets of measures. The first includes the initiatives to improve the quality of banks' reported capital, by limiting the set of instruments that qualify as regulatory capital. The most attention in this area has been given to limiting bank reliance on intangibles, such as DTAs and goodwill, which are widely seen as having poor loss-absorption properties. We examine whether this consensual view is confirmed in the data and again find mixed evidence: while there is some evidence that intangibles, such

[9]Theoretically, in the context of Merton model of credit risk, a bank's economic capital and its variability over time, should be the sufficient statistics in assessing the prospects of bank distress.

[10]Defined as banks with balance sheet size below $10 billion. See Section 4.3.1 for further explanation of the threshold determination.

as DTAs and goodwill, have poor loss-absorption properties, the evidence is not uniform across samples and event types. We find that DTAs have the strongest positive association with bank distress for large banks in Europe, but are otherwise a relatively insignificant predictor of bank distress in other samples. Goodwill, on the other hand, exhibits a strong positive association with bank distress for the small (non-IRB) banks in the U.S.

The second set of Basel III initiatives, aimed at improving the correspondence between regulatory and economic capital is the increasing reliance on the risk-insensitive capital measures, such as the LR. The main difference between LR and RWCR - in particular for the large (IRB) banks - is their denominator. While the calculation of the RWA denominator in RWCR leaves banks with substantial degree of discretion, the risk-insensitive denominator in the LR is based on less discretionary inputs, such as the total balance sheet size.

Is discretion afforded by the IRB approach really a culprit for the discrepancy between regulatory and economic capital? We address this question by examining the association between bank distress and Basel RW, while controlling for the LR. This test is based on the fact that RWs are the only new source of information in the RWCR relative to the LR. Our key finding is this: the association between RWs and bank distress is significant only in the subset of the small (non-IRB) banks, while it is statistically insignificant for the large (IRB) banks. This finding is consistent with a concern that the IRB banks may apply discretion in ways that hamper the association between their reported and real risks.

We provide further evidence in support of this explanation by showing that in response to the negative capital shocks, RWs of large (IRB) banks tend to fall, thus mitigating the effect of the shock on the banks' risk-weighted capital ratio (RWCR). We show that the downward movement in RWs attenuates the effect of a capital shock on the large bank's RWCR by 0.3pp for each 1pp fall in bank capital. In contrast, we show that for the small (non-IRB banks), which have less discretion in reporting their RWs, the relationship between the negative capital shocks and RW is significantly weaker or disappears.

The evidence presented in this chapter highlights the discrepancy between banks' *reported* capital and its economic (conceptual) counterpart, especially in the case of large (IRB) banks. This confirms the concerns that have led to the recent regulatory push towards (1) improving the quality composition of regulatory capital and (2) increasing reliance on *risk-insensitive* measurement of bank capital, encapsulated in the LR. While the introduction of the minimum LR requirements represents one of the major moves towards less risk sensitive capital requirements in the Basel III, the authorities are currently considering a variety of additional measures, whose aim is to limit risk-sensitivity of the RWAs. This includes the introduction of floors on several types of exposures, such as residential mortgages, to which banks typically assign relatively low risk weights.[11] While the evidence in this chapter provides some support for these initiatives, further research is needed to examine other potential consequences of their introduction.

Appendix

Basel III Phase-In Arrangements

Table 4.9 (next page) outlines some of the key regulations in Basel III.

[11] http://zanders.eu/en/latest-insights/why-dutch-banks-fear-basels-new-capital-floor/

Table 4.9 – Basel III phase-in arrangements

Phases		Year						
		2013	2014	2015	2016	2017	2018	2019
Capital	**Leverage Ratio**			Start of disclosure in January 2015				
	Minimum Common Equity Capital Ratio	3.5	4	4.5	4.5	4.5	4.5	4.5
	Capital Conservation Buffer				0.625	1.25	1.875	2.5
	Minimum common equity plus capital conservation buffer	3.5	4	4.5	5.125	5.75	6.375	7
	Phase-in of deductions from CET1[b]		20	40	60	80	100	100
	Minimum Tier 1 Capital	4.5	5.5	6	6	6	6	6
	Minimum Total Capital	8	8	8	8	8	8	8
	Minimum Total Capital plus conservation buffer	8	8	8	8.625	9.25	9.875	10.5
	Capital instruments that no longer qualify as non-core Tier 1 capital or Tier 2 capital			Phased out over 10-year horizon				
Liquidity	**Liquidity coverage ratio - minimum requirement**			60	60	80	90	100
	Net stable funding ratio						Introduce minimum standard	

Notes:
[a] The table is based on the BIS Basel III phase-in arrangements, available at: `http://www.bis.org/bcbs/basel3/basel3_phase_in_arrangements.pdf`. All amounts are stated in %.
[b] The most prominent examples of deductions include deferred tax assets (DTA), goodwill, and other intangibles.

CHAPTER 5

Effective Macroprudential Policy: Cross-Sector Substitution from Price and Quantity Measures[1]

"Effective regulation, one that actually bites, is likely to penalize those within the regulated sector, relative to those just outside, causing substitution flows towards the unregulated."

— Charles Goodhart

5.1 Introduction

Macroprudential policy is alive and kicking. It is being used actively both in emerging market economies and – following the financial crisis – in advanced economies. This includes measures that apply directly to lenders, such as countercyclical capital buffers or capital surcharges, and restrictions that apply to borrowers, such as loan-to-value (LTV) and loan-to-income (LTI) ratio caps. Most macroprudential measures implemented around the globe between 2000 and 2013 apply to the banking sector only, including the borrower based measures (International Monetary Fund (IMF), 2013, Global Macroprudential Policy Instruments Database).

The widespread use of macroprudential policy is aimed at reducing systemic risks. Yet the implementation of national sector-based measures may be subject to a boundary problem, causing substitution flows to less regulated parts of the financial sector (Goodhart, 2008; Aiyar et al., 2014). Specifically, macroprudential

[1]This chapter is based on Cizel et al. (2016), co-authored with Jon Frost, Aerdt Houben, and Peter Wierts (all from *De Nederlandsche Bank*).

policy may have the consequence of shifting activities and risks both to: (i) foreign entities (e.g. bank branches and cross-border lending) and (ii) non-bank entities (e.g. shadow banking, also referred to as market-based financing). Whereas several papers have estimated intended effects of macroprudential policies (MaPs) on variables such as credit growth and housing prices, and whether measures leak to foreign banks, cross-sector substitution effects have – to the best of our knowledge – not yet been tested empirically.

This paper aims to fill this gap. It investigates whether macroprudential policies (MaPs) lead to substitution from bank-based financial intermediation to non-bank intermediation. In addition, it uses event study methodology to shed light on the timing of the effects of policy measures on bank and non-bank intermediation around implementation dates. Moreover, we contribute to the literature by distinguishing between the effects of quantity versus price-based instruments and lender versus borrower-based instruments, given that the effects may differ. We also check whether results differ for advanced economies (AEs) versus emerging market economies (EMEs) and bank versus market-based financial systems.

Results confirm that macroprudential policies reduce bank credit growth. In the 2 years after the implementation of MaPs, bank credit growth falls on average by 7.7 percentage points relative to the counterfactual of no measure. This effect is much stronger in EMEs than in AEs. Beyond this, the analysis indicates that quantity-based measures have much stronger effects on credit growth than price-based measures, both in advanced and emerging market economies. In cumulative terms, quantity measures suppress bank credit growth by 8.7 percentage points over 2 years relative to the counterfactual of no policy change. These results are in the same order of magnitude as those of Morgan et al. (2015), who find that economies with LTV polices (which we classify as a quantity constraint) have experienced residential mortgage loan growth of 6.7% per year, while non-LTV economies have experienced 14.6% per year. Moreover, for the effect on bank credit, our results have the same order of magnitude as those of Cerutti et al. (forthcoming), who find stronger effects in emerging market economies than in advanced economies, just as we do.

Our main contribution to the literature is in our findings on substitution effects: the effect of MaPs on bank credit is always substantially above the effect on total credit to the private sector. Whereas bank credit growth falls on average by 7.7 percentage points relative to the counterfactual of no measure, non-bank credit increases after the implementation of MaPs so that total credit falls by 4.9 percentage points on average. Next to this general result we find remarkable differences between country groups and instruments. First, substitution effects are stronger in AEs. This is in line with expectations given their more developed financial systems, with a larger role for market-based finance. Second, substitution effects are much stronger in the case of quantity restrictions, which are more constraining than price-based measures. Moreover, we find strong and statistically significant effects on specific forms of non-banking financial intermediation, such as investment fund assets.

Our paper builds on a rapidly expanding literature on macroprudential policy. While the concept of macroprudential policy can be traced back at least to the late 1970's (Clement, 2010), it has become a common part of the policy lexicon in the first decade of this millennium. The crisis has led not only to much more interest in the macroprudential approach, but also to active use of macroprudential instruments around the world. Galati and Moessner (2013, 2014) provide an overview of the literature, emphasizing the objectives, instruments and analytical underpinnings of the macroprudential approach. The ESRB (2014) has released a handbook for operationalizing the macroprudential toolkit and the (IMF) a staff guidance note.

Recently, the active use of instruments has spawned a growing empirical literature on the effectiveness of macroprudential policies, both in individual country or regional cases and in global panels (Arregui et al., 2013). The most comprehensive approach is that of Cerutti et al. (forthcoming), who use an IMF survey to document macroprudential policies for 119 countries over the 2000-13 period. They find that the implementation of such instruments is generally associated with the intended lower impact on credit, but that the effects are weaker in financially more developed and open economies. Bruno and Shin (2014) find that macroprudential policies employed in Korea to deal with the effects of cross-border capital flows – such as the "macroprudential levy" – helped to reduce the sensitivity of capital flows into Korea to global conditions. Krznar and Morsink (2014) establish that recent rounds of macroprudential policy tightening in Canada have reduced mortgage credit growth and house price growth. Lim et al. (2011) shows that for 49 countries reviewed, macroprudential instruments helped to reduce pro-cyclicality, meaning a reduced sensitivity of credit conditions to GDP growth.

Because of the inherent difficulties in establishing the effects of measures at a macro level, a number of studies have used micro-level data on behavioral effects of macroprudential policies. For example, by exploiting bank-specific shocks to capital buffers, Jiménez et al. (2012) show that Spain's dynamic provisioning requirements helped to smooth cycles in the supply of credit. With Korean data on housing and mortgage activity, Igan and Kang (2012) find that the tightening of Debt-to-Income

(DTI) and LTV limits have a significant and sizeable impact on transaction activity and house price appreciation.

Yet in addition to its intended effects, macroprudential policy may leak. Aiyar et al. (2014) and Reinhardt and Sowerbutts (2015) find that foreign borrowing increases after home authorities take macroprudential actions targeting domestic banks' capital. Similarly, Cerutti et al. (forthcoming) find some evidence of greater cross-border borrowing after macroprudential measures are taken. But macroprudential policy may also increase cross-sector substitution (Goodhart, 2008). The (IMF) finds that more stringent capital requirements are associated with stronger growth of shadow banking. On the latter substitution effect, an innovation in our paper is the use of both net flow measures and an event study methodology to shed light on the size and timing of the effect. Our empirical framework builds on work that has sought to explain credit growth, for instance to understand credit rationing and the monetary transmission mechanism (Berger and Udell, 1992; Gertler and Gilchrist, 1991; Kashyap et al., 1993). In line with Frost and Van Tilburg (2014), we control for macroeconomic fundamentals to filter out effects of policy on credit growth in a cross-country panel setting.

Our results do not tell whether substitution effects reduce or increase systemic risks. The former outcome may be expected, as risks may shift to institutions that are less leveraged and less subject to maturity mismatch. But this need not be the case, as market failures and systemic risks may also arise outside the regulated banking sector. Specifically, nonbank financial institutions may contribute to procyclical leverage (Adrian, 2014; Adrian and Shin, 2009); may amplify the impact of price changes and flows (Feroli et. al., 2014), and may be subject to misaligned incentives that influence the overall risk in the system (Rajan, 2006). A macroprudential approach aims to address such systemic risks in a broad, consistent manner, by addressing the underlying mechanisms and regulating both activities and entities (Adrian, 2014; Board, 2014; , IMF). Overall, our findings underline the relevance of such a broad approach towards monitoring and addressing systemic risks, especially for advanced economies. Earlier findings on cross-border leakages indicate that macroprudential policy should not take a narrow national perspective, as this would fail to internalize cross-border substitution effects. Our results on cross sector substitution complement these findings, as they indicate that macroprudential policy should not take a narrow sectoral perspective. In this context, Schoenmaker and Wierts (2015) propose an integrated approach for highly leveraged entities and activities across the financial system in order to internalize cross-sectoral substitution effects. A similar approach can be envisaged for maturity and liquidity mismatches, interconnectedness and misaligned incentives related to too-big-to fail (European Systemic Risk Board, 2013).

The rest of the paper is organized as follows. Section 5.2 describes the data. Section 5.3 investigates the substitution between bank and non-bank credit by estimating whether macroprudential measures affect the flows of bank and non-bank credit as a percentage of total credit. Section 5.4 provides a complementary approach, by estimating the effect of macroprudential policies on both series (and additional non-bank series) directly with an event study methodology. It also distinguishes between different types of macroprudential measures (price versus quantity-based, and borrower versus lender-based) and different country groups. Robustness checks are presented in section 5.5. Section 5.6 concludes.

5.2 Data

The analysis in this paper is based on three types of country-level data: (A) information on bank and non-bank credit, (B) the dates and types of macroprudential policy measures, and (C) indicators of macroeconomic fundamentals. The dataset is also available in the online appendix of this paper[2].

5.2.1 Private credit to the non-financial sector

We use a measure of bank and non-bank credit from the Bank for International Settlements (BIS) database on private non-financial sector credit (Dembiermont et al., 2013). The database contains quarterly series of private credit data for a selection of 40 economies over the last 40 years. Private credit covers all loans and debt securities to non-financial corporations, households and non-profit institutions serving households. Bank credit is defined as all loans and debt securities held by domestic and foreign banks (subsidiaries and branches). Non-bank credit encompasses loans and debt securities held by all other sectors of the economy (e.g. insurers, pension funds, investment funds, other firms, households, etc.) and, for some countries, direct cross-border credit by foreign banks. The presence of direct cross-border lending in the non-bank credit measure may hamper the cross-sectoral focus of this study because it may conflate loans by domestic non-banks and foreign banks abroad. In the Appendix 5.A we show, however, that the direct cross-border lending amounts to less than 5% of non-bank credit for the aggregate sample of BIS reporting countries.

[2]The online appendix can be found at http://www.jankocizel.com/research/macroprud/.

For this reason, movements in the non-bank credit series are expected to primarily reflect the changes in the provision of credit by non-bank financial institutions, rather than by foreign banks.

A shortcoming of the BIS database is its relatively low geographic coverage, as it contains only 40 economies, most of which are advanced. In addition, the database provides no information on the breakdown of the types of non-bank credit providers. We thus complement the private credit data from the BIS with information on the balance sheet sizes of banks and of various types of non-bank financial institutions, which we obtain from the World Bank's Financial Development Database (Čihák et al., 2012, see). The cross-section coverage of the database ranges from about 80 countries in the case of investment and pension funds, to over 100 countries in the case of banks and insurance companies. The database covers the period 1980-2012 for different series[3].

Figures 5.1(a) and 5.1(b) illustrate the dynamics of bank and non-bank credit flows, both in AEs and EMEs. It indicates a more cyclical pattern for bank credit than for non-bank credit.

We measure the substitution of credit between banks and non-banks as the quarterly net sectoral credit flow, defined as the difference between the quarterly change in bank credit and the quarterly change in non-bank credit, scaled by total credit:

$$\begin{aligned}&[\text{Quarterly Net Sectoral Credit Flow}]_{ct} = \\ &100 * \frac{\frac{1}{4}[\Delta^{YtY}\text{Bank Credit}]_{ct} - \frac{1}{4}[\Delta^{YtY}\text{Non-Bank Credit}]_{ct}}{[\text{Total Credit}]_{c,t-4}}\end{aligned} \tag{5.1}$$

Positive values of the measure indicate that growth in bank credit outpaces growth in non-bank credit, while negative values indicate more substitution to non-banks[4]. The nominal net flows in credit (the numerator) are scaled by the previous years' stock of total credit (the denominator). On average, the measure is higher in EMEs than in AEs (Table 5.1, Panel A). This is as expected given that the numerator of our measure contains level changes, and the share of bank credit in total credit is much higher in EMEs than in AEs.

[3]In what follows, advanced and emerging market economies are defined according to the most recent IMF World Economic Outlook, IMF (WEO) classification. Market-based financial systems have a share of non-bank credit in total credit is above the sample-wide median. For more analysis on market versus bank-based systems, see Gambacorta et al. (2014).

[4]A drawback of measuring the relative shift between bank and non-bank credit is that this does not indicate whether the shift is driven by one of these components or both. We therefore complement this analysis with estimates of the direct effect of MaPs on bank and non-bank credit.

Table 5.1 – Summary statistics on credit, macroprudential policies and macroeconomic indicators

	1997-2014, Quarterly		
	Advanced Economies	Emerging market Economies	Whole Sample
Panel A: Credit Series			
Bank Credit to Private Sector (% of GDP), Source: BIS	84.79	60.41	77.83
	(36.86)	(42.48)	(40.08)
Non-Bank Credit to Private Sector (% of GDP), Source: BIS	55.78	9.32	42.49
	(41.25)	(14.18)	(41.39)
Investment fund assets to GDP (%), Source: WB-GFDD	31.11	6.38	21.74
	(68.26)	(9.68)	(55.43)
Bank Credit, YtY % Change, Source: BIS	6.47	10.53	7.65
	(11.18)	(16.35)	(13.03)
Non-Bank Credit, YtY % Change, Source: BIS	7.33	11.59	8.57
	(13.95)	(31.87)	(20.90)
Total Credit, YtY % Change, Source: BIS	6.68	9.78	7.59
	(9.98)	(15.10)	(11.79)
Net Sectoral Credit Flow, % of Total Credit, Source: BIS	1.29	5.76	2.59
	(6.36)	(11.10)	(8.29)
Panel B: Macroprudential Policy Indices			
Overall Index	1.56	2.00	1.83
	(1.41)	(1.63)	(1.56)
Quantity-Based Regulatory Index	1.57	1.96	1.81
	(1.43)	(1.52)	(1.50)
Price-Based Regulatory Index	0.16	0.25	0.22
	(0.38)	(0.51)	(0.46)
Panel C: Other Macroeconomic Indicators			
Inflation, average consumer prices, Source: IMF-WEO	2.91	7.27	6.00
	(2.75)	(7.45)	(6.74)
YtY Real % Growth in GDP, Source: IMF-IFS,	3.58	5.59	5.00
	(7.48)	(7.78)	(7.75)
Current account balance, Source: IMF-WEO	1.90	-5.03	-3.04
	(11.53)	(10.35)	(11.15)
General government net lending/borrowing,	-0.10	-2.14	-1.54
Source: IMF-WEO	(7.28)	(5.56)	(6.18)
Equity inflows, % of GDP, Source: IMF-IFS	6.17	1.43	2.79
	(11.56)	(4.81)	(7.71)
Debt inflows, % of GDP, Source: IMF-IFS	11.78	1.52	4.47
	(33.73)	(8.11)	(19.89)
CB Lending Rate (in %), Source: IMF-IFS	7.26	16.73	13.82
	(4.65)	(9.93)	(9.70)
YtY % Growth in CB Assets, Source: WB-GFDD	8.97	13.00	11.81
	(47.49)	(43.89)	(45.02)
GDP per capita, current prices, Source: IMF-WEO	29042	2943	10433
	(17691)	(2951)	(15342)
Banking crisis dummy	0.19	0.03	0.07
(1=banking crisis, 0=none), Source: WB-GFDD	(0.39)	(0.16)	(0.26)

Notes:
[1] Standard deviations in parentheses.

Figure 5.1(c) provides further insight into the dynamics of the measure both for AEs and EMEs. It indicates a cyclical pattern in net sectoral credit flows. Figure 5.2 provides a histogram of the net credit flow measure. The distribution of the measure is positively skewed, with average and the mode slightly above 0.

To limit the influence of outliers, we winsorize all credit-related variables at the 1% level for each tail of their distribution. We also exclude the observations for Argentina, which experienced a prolonged sovereign distress episode covering much of our sample period.

5.2.2 Macroprudential Policy Events

The information on the use of macroprudential policies (MaPs) across countries and over time comes from Cerutti et al. (forthcoming), who create a set of indicator variables that measure the implementation of various MaPs in 120 countries over the period of 2000-13. Their database is constructed from responses to the IMF's Global Macroprudential Policy Instruments Database, IMF (GMPI) survey, reported by the participating countries' financial authorities (IMF, 2013). The analysis covers 12 categories of MaPs, described in Table 5.2. Cerutti et al. (forthcoming) classify these as lender-based or borrower-based. Lender-based policies are those aimed at financial institutions' assets or liabilities and include, for example, loan-loss provisioning practices, leverage, and capital buffers. Borrower-based measures are those aimed at borrowers' leverage and financial positions, and cover LTV and LTI caps. Limits on foreign currency and domestic currency loans and reserve requirements have been the norm in EMEs, whereas leverage ratios and limits on interbank exposures are most frequently applied in AEs. Overall, the most popular lender-based MaPs in both AEs and EMEs are concentration limits, which restrict the fraction of bank assets tied to a particular type of borrowers.

Inspection of the underlying qualitative answers in the IMF GMPI database indicates that all MaPs are primarily aimed at depository institutions (banks), including the borrower-based measures. Our hypotheses on substitution effects between bank and non-bank credit can therefore be tested by including all MaPs simultaneously.

The effect of MaPs may depend on whether a measure acts as a quantity constraint on credit, which limits the volume of a particular activity, or as a price constraint, which affects the average cost of engaging in this activity, mostly by increasing resilience. We thus categorize MaPs in the dataset into price and quantity-based

Table 5.2 – Classification of Macroprudential Policies

Abbreviation	Name	Number of Events	Borrower/ Lender-Based	Price/ Quantity Restriction
LTV	Loan-to-Value Ratio	32 [18%]	Borrower	Quantity
DTI	Debt-to-Income Ratio	23 [13%]	Borrower	Quantity
DP	Time-Varying/Dynamic Loan-Loss Provisioning	10 [5%]	Lender	Price
CTC	General Countercyclical Capital Buffer/Requirement	6 [3%]	Lender	Price
LEV	Leverage Ratio	13 [7%]	Lender	Quantity
SIFI	Capital Surcharges on SIFIs	7 [4%]	Lender	Price
INTER	Limits on Interbank Exposures	16 [9%]	Lender	Quantity
CONC	Concentration Limits	22 [12%]	Lender	Quantity
FC	Limits on Foreign Currency Loans	15 [8%]	Lender	Quantity
RR	Reserve Requirement Ratios	12 [7%]	Lender	Quantity
CG	Limits on Domestic Currency Loans	7 [4%]	Lender	Quantity
TAX	Levy/Tax on Financial Institutions	17 [9%]	Lender	Price

measures and perform all subsequent analyses on both groups separately. Table 5.2 also provides this classification. Examples of price-based policies include dynamic provisioning requirements and taxes on financial institutions. Examples of quantity-based measures are limits on interbank and foreign currency exposures, both of which act as a cap on the balance sheet exposures to the particular asset classes. The distinction between quantity and price classifications is admittedly fuzzy in some cases. For example, assuming that the supply of bank capital is constrained, we classify the leverage ratio as a quantity measure, since it effectively caps the balance sheet size of the affected entity. A leverage ratio cap could however also be seen as a price-based measure, since the bank could in principle expand its balance sheet by raising new capital, which would affect the average cost of funding. As a robustness check, we perform the analyses with alternative price/quantity classifications; the corresponding results are reported in the online appendix.

Panel B of Table 5.1 provides summary statistics for MaP indices, which are defined as the sum of MaPs of a given classification, implemented by a country in a given period. On average, AEs and EMEs have 1.6 and 2 MaPs in place in a given year, respectively.

We measure MaPs as yearly dummy variables for individual measures[5]. Figure 5.3 provides an overview of MaPs across countries in the dataset. Circles in the

[5] The database of Cerutti et al. (forthcoming) records the number of MaPs of a particular type implemented by a country at a given point in time. Macroprudential policy events are defined as changes in the number of MaPs.

graph mark the periods of the implementation of MaPs. The circle size corresponds to the number MaPs implemented by a country in that year. The color of circles denotes the percentage of quantity-based MaPs. In total there are 171 MaPs in the dataset, 77% of which are quantity-based. Most events, in particular in AEs, are clustered during the period 2007-13. Prior to that MaPs were implemented mostly in EMEs.

5.2.3 Macroeconomic Fundamentals

In the subsequent analysis, we model the baseline growth rates of credit by using a number of macroeconomic variables as controls. While it is inherently difficult to distinguish between factors influencing the demand and supply for credit, we expect that higher GDP growth should be associated with higher demand for credit by firms and households. Credit supply should be increased by higher foreign capital inflows (into the banking sector and capital markets), and decreased by inflation and higher government borrowing (due to crowding out effects). The sources of these variables are the IMF's WEO and International Financial Statistics databases. Panel C of Table 5.1 provides the summary statistics for the variables used.

5.3 Cross-Sectoral Substitution due to Macroprudential Measures

5.3.1 Methodology

This section studies the cross-sector leakages of MaP in the provision of credit to the private sector. In line with the "boundary hypothesis", the implementation of a MaP directed at banks is expected to shift the relative provision of credit towards unregulated or less regulated credit providers, referred to as non-banks[6].

We measure the substitution of credit as changes in net sectoral credit flow, defined in the previous section. To the extent that MaPs increase the relative cost of bank credit, we expect them to prompt a contraction in the net sectoral credit flow measure, which indicates a relative shift from bank to non-bank credit. (Section 5.4 also estimates the direct effect of MaPs on different credit categories.)

[6] In economic theory, the flow of finance between bank and non-bank sectors depends on the expected risk-adjusted rate of return to investors in the two sectors. A shock that reduces the expected returns in one sector causes the provision of credit to shift towards the (relatively) unaffected sector.

Linking cross-sector credit substitution to MaPs raises identification issues. One concern with our interpretation is that cross-sector shifts in credit supply may be the outcome of other factors asymmetrically impacting the cost of capital or expected investment returns of different credit providers. If such factors move in tandem with MaP implementation this creates an identification problem.

At least two factors may blur the effects attributed to MaPs. The first is the occurrence of banking crises. As noted in section 5.2, most MaPs occur during and after the period of the Global Financial Crisis (GFC), which was particularly detrimental to the balance sheets of banks. Indeed, the severity of the GFC for banks could result in cross-sector shifts in credit provision even in the absence of MaP implementation. Moreover, authorities responded to the GFC with a set of expansionary monetary and fiscal policies, aimed inter alia to restore the viability of and confidence in the banking sector. To the extent that such policies coincided with MaPs, their separate impact is difficult to identify.

Second, changes in monetary policies – through policy rates and unconventional measures – may have asymmetric effects on different categories of credit providers, in a direction that is not clear a priori. For example, periods of low policy interest rates may directly benefit bank credit, but may also motivate banks to "search for yield," by investing in alternative high-yield and high-risk investments (see Buch et al., 2014 for banks; see Azis and Shin, 2014 for debt market issuance and asset managers). Likewise, changes in central bank balance sheets stemming from unconventional monetary policy measures may reflect either direct funding to banks, or changes in holdings of publically traded securities or non-bank debt.

We address the above identification challenges in the following ways. First, we control for the occurrence of systemic banking crises by including the banking crisis indicator of Laeven and Valencia (2013) as a control variable in all subsequent empirical specifications. The crisis indicator flags those country-quarter observations during which a country experienced a systemic banking crisis. Since banking crises in Laeven and Valencia (2013) are defined with reference to the use of various crisis management tools, such as deposit guarantees and government recapitalizations of failed banks, the inclusion of this indicator deals with the concern that our results on MaPs might be picking up the effects of other policies that occurred during the same period of time.

Second, we control for changes in monetary policy in two ways. First, our empirical specifications include year-on-year changes in the monetary policy rate as one of the explanatory variables. Second, we control for unconventional monetary policies by including a variable that measures year-to-year changes in central banks' balance sheet size relative to GDP (see Pattipeilohy et al., 2013).

With these caveats in mind, we estimate the following specification:

$$NetFlow_{c,t} = \alpha_c + \beta_t + \theta_1 BankCrisis_{c,t} + \theta_2 \Delta MonetaryPolicy_{c,t} + \theta_3 \Delta MaP_{c,t} + \epsilon_{c,t} \tag{5.2}$$

where $NetFlow_(c,t)$ is the net sectoral credit flow (defined in Section 5.2) for country c and year t and α and β are country and time dummies. $BankCrisis$ is a dummy variable capturing systemic banking crises. In line with the above discussion, its expected sign is negative. $\Delta MonetaryPolicy$ indicates changes in the central bank policy rate and the central bank balance sheet size. The expected sign of the coefficient is ambiguous for both. We estimate the coefficients in the above specification using the within panel estimator and we cluster the standard errors by country to allow for serial correlation in residuals.

Most importantly for us, ΔMaP indicates the activation of macroprudential policies, as previously defined. A positive change of the index in a particular year represents a tightening of the MaP stance, which we expect to be associated with a higher degree of cross-sectoral leakage and thus with lower values of net sectoral credit flows.

As discussed in section 5.2, we also split the baseline measure of the MaP stance between quantity and price-based measures. We measure changes in quantity and price-based MaPs by year-to-year changes in the respective MaP indices, again constructed as the number of tools falling into either of the two categories that are implemented in a country at a given point in time.

5.3.2 Results

Table 5.3 reports estimation results on the impact of the overall changes in macroprudential policies. In line with the boundary hypothesis, MaP coefficients are negative across all subsamples, indicating that net sectoral credit flows move in favor of non-banks following the implementation of macroprudential policies directed at banks. The magnitude of the coefficient for the overall sample is -0.26, implying that during the first year after MaP implementation the net sectoral credit flows move by about 1 percentage point (hereafter pp) of total credit in favor of non-banks. The effect is statistically significant, especially in the case of AEs.

As expected, coefficients for the banking crisis indicator are negative and statistically significant for most samples. Banking crises thus appear to hit bank credit

Table 5.3 – Substitution from bank to non-bank credit

	Net Bank/Non-Bank Credit Flow				
	ALL (1)	AE (2)	EME (3)	Market-Based (4)	Bank-Based (5)
[Banking Crisis Indicator]	-1.18***	-0.59***	-2.48***	-0.55***	-1.37***
	(0.11)	(0.09)	(0.36)	(0.20)	(0.14)
Δ^{YtY} MaP Index	-0.26**	-0.27***	-0.30	-0.34*	-0.24*
	(0.13)	(0.10)	(0.29)	(0.21)	(0.16)
Δ^{YtY}[CB Lending Rate]	0.00	0.04***	-0.09***	0.03***	-0.08***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
Δ^{YtY}[Log of CB BS Size]	-0.46***	-0.68***	0.54*	-0.08	-0.58***
	(0.11)	(0.08)	(0.35)	(0.18)	(0.14)
Constant	0.61***	0.63***	-0.15	0.26	0.78**
	(0.23)	(0.16)	(0.83)	(0.33)	(0.31)
R-squared	0.13	0.12	0.29	0.15	0.15
Obs.	3224	2291	933	1061	2163
# of Countries	31	22	9	10	21

Notes:
Columns 1-3 report the OLS results for the following specification:

$$NetFlow_{c,t} = \alpha_c + \beta_t + \theta_1 BankCrisis_{c,t} + \theta_2 \Delta MonetaryPolicy_{c,t} + \theta_3 \Delta MaP_{c,t} + \epsilon_{c,t}$$

where NetFlow is defined as:

$$[NetFlow]_{ct} = 100 * \frac{\frac{1}{4}[\Delta^{YtY}\text{Bank Credit}]_{ct} - \frac{1}{4}[\Delta^{YtY}\text{Non-Bank Credit}]_{ct}}{[\text{Total Credit}]_{c,t-4}}$$

and $BankCrisis$ is a dummy variable capturing the presence of systemic banking crisis, $\Delta MonetaryPolicy$ measures changes in the monetary policy, and $\Delta MacroPrud$ measures changes in the MaP stance.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

to a much larger extent than non-bank credit – likely through credit supply. The impact of banking crises is large: on average they reduce net credit flows from banks by about 5pp of total credit per annum. The effect is particularly strong in EMEs, where it amounts to about 10pp per annum.

The association between net credit flows and central bank interest rates is ambiguous: while it is positive in AEs, it is negative in EMEs and insignificant in the pooled sample. Expansion in central bank balance sheets is negatively related to net credit flows across most samples. In the overall sample, a 1% increase in central bank assets is associated with 2pp per annum shift in net credit flows originating from banks. That is: increases in central bank balance sheets appear to stimulate a relative shift from bank to non-bank credit. The association is particularly strong in AEs and in bank-based financial systems.

Next, Table 5.4 reports results for the specification distinguishing between quantity and price-based measures. The coefficients for MaPs are negative and statistically

Table 5.4 – Substitution from bank to non-bank credit for price and quantity measures

	Net Bank/Non-Bank Credit Flow				
	ALL (1)	AE (2)	EME (3)	Market-Based (4)	Bank-Based (5)
[Banking Crisis Indicator]	-1.20***	-0.61***	-2.51***	-0.59***	-1.40***
	(0.11)	(0.09)	(0.36)	(0.20)	(0.14)
Δ^{YtY} [MaP Quantity-Based Index]	-0.49***	-0.45***	-0.38	-0.69***	-0.42**
	(0.15)	(0.12)	(0.34)	(0.25)	(0.18)
Δ^{YtY} [MaP Price-Based Index]	0.56**	0.12	0.81	0.36	0.71**
	(0.26)	(0.20)	(0.74)	(0.42)	(0.34)
Δ^{YtY}[CB Lending Rate]	0.00	0.04***	-0.09***	0.03***	-0.08***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
Δ^{YtY}[Log of CB BS Size]	-0.46***	-0.68***	0.52*	-0.09	-0.58***
	(0.11)	(0.08)	(0.35)	(0.18)	(0.14)
Constant	0.62***	0.63***	-0.15	0.26	0.79**
	(0.23)	(0.16)	(0.83)	(0.33)	(0.31)
R-squared	0.14	0.13	0.29	0.16	0.16
Obs.	3224	2291	933	1061	2163
# of Countries	31	22	9	10	21

Notes:
Columns 1-3 report the OLS results for the following specification:

$$NetFlow_{c,t} = \alpha_c + \beta_t + \theta_1 BankCrisis_{c,t} + \theta_2 \Delta MonetaryPolicy_{c,t} + \theta_3 \Delta MaP_{c,t} + \epsilon_{c,t}$$

where NetFlow is defined as:

$$[NetFlow]_{ct} = 100 * \frac{\frac{1}{4}[\Delta^{YtY}\text{Bank Credit}]_{ct} - \frac{1}{4}[\Delta^{YtY}\text{Non-Bank Credit}]_{ct}}{[\text{Total Credit}]_{c,t-4}}$$

and $BankCrisis$ is a dummy variable capturing the presence of systemic banking crisis, $\Delta MonetaryPolicy$ measures changes in the monetary policy, and $\Delta MacroPrud$ measures changes in the MaP stance.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

significant for quantity measures, and are positive and statistically insignificant for price measures. In the overall sample, the effect of quantity measures indicate a 2pp relative shift in the provision of credit towards non-banks during the first year after the implementation. The effect is particularly strong in market-based economies (3pp).

Taken together, the results in this section provide evidence that is consistent with the boundary hypothesis: the implementation of macroprudential policies is linked to a relative shift in the provision of credit from banks to non-banks. The substitution effect is especially pronounced for quantity-based measures directed at banks and is absent for price-based measures.

5.4 Event Study of Macro-Prudential Policy Interventions

5.4.1 Methodology

This section further examines the effects of MaPs by studying the behavior of bank credit, non-bank credit, total credit, and net sectoral credit flows, before and after the implementation of MaPs. Including the timing of the effects is important given that market participants may react to measures that have been announced but that have not yet taken effect. Moreover, macroprudential authorities may respond to periods of high or low credit growth by tightening or easing MaPs. We therefore apply a leads-and-lags model (Atanasov and Black, 2016). This model is suitable for checking pre-treatment and post-treatment trends relative to control groups of entities (in our case countries). Pre-treatment trends that are statistically different from 0 may be indicative of endogeneity issues, since the occurrence of the event may then be explained by the abnormal movements in the dependent variable (in our case credit) during the pre-event period.

As discussed in Section 5.2, MaP events are defined as the year in which a country implements a macroprudential tool. To isolate the movements in credit flows that can be attributed to MaPs, we adjust the actual credit growth by a counterfactual rate of credit growth that would have prevailed in absence of a MaP. We then use event study methodology to examine the divergence between the resulting adjusted and actual growth rates around MaPs.

Let denote credit growth by sector s in country c at time t. The excess rate of growth $y^s_{c,t}$is defined as:

$$\hat{y}^s_{c,t} = y^s_{c,t} - E[y^s_{c,t}] \tag{5.3}$$

We assume that the expected rate of growth, $E[y^s_{c,t}]$, is a linear function of a covariate vector x, which controls for macroeconomic conditions within a country. We also allow for country-specific time-invariant determinants of credit/asset growth, μ_c, as well as for common shocks, μ_t. The resulting specification for the expected credit/asset growth in sector s is then:

$$E[y^s_{c,t}] = \alpha^s_t + \mu^s_c + x'_{c,t}\beta^s \tag{5.4}$$

where β^s denotes a vector of coefficients of the covariate vector x. There is currently little theoretical consensus on the set of economic measures that define the expected credit growth rates for banks and non-banks. As a result, theory offers only limited guidance on the composition of the covariate vector x. Our choice of the covariate vector x thus draws on the existing empirical literature that explores the determinants of total credit (see Frost and van Tilburg, 2014) and bank credit (see Berger and Udell, 1992; Gertler and Gilchrist, 1991; Kashyap et al., 1993); we are not aware of comparable studies explaining non-bank credit or net sectoral credit flows. Specifically, we control for the presence of systemic banking crises, GDP growth, the current account balance, gross capital inflows, central bank lending interest rates and the growth in central bank assets.

Next, let τ denote a time at which a MaP event takes place, and define an indicator function that equals 1 if a MaP event occurs between i and $i+1$ time units from time t, and zero otherwise:

$$1_{\tau \in (t+i, t+i+1]} = \begin{cases} 1, & \text{if } \tau \in (t+i, t+i+1] \\ 0, & \text{otherwise} \end{cases} \tag{5.5}$$

A set of excessive growth rates around MaP events can then be obtained by estimating the following expected growth rate (EGR) specification:

$$y^s_{c,t} = \alpha^s_t + \mu^s_c + x'_{c,t}\beta^s + \sum_i \phi^s_i 1_{\tau \in (t+i, t+i+1]} + \epsilon^s_{c,t}. \tag{5.6}$$

In the above specification, ϕ_i measures the excessive growth in sector s of country c, i periods before (for the negative values of i) or after (for the positive values of i) the MaP event. We estimate the coefficients in the above specification using the within panel estimator and we cluster the standard errors by country to allow for serial correlation in residuals. We lag all variables in the covariate vector x by one year, to mitigate concerns of endogeneity. In cases in which a MaP event is preceded by another MaP event within two years prior to its deployment, we exclude it from the analysis and only consider the first event in the sequence[7].

The main remaining identification assumption of this section is that after controlling for the set of observables in x, the authorities' decision on the implementation of macroprudential policies is independent from any additional factors that might jointly determine the growth of the bank and non-bank sectors. To the extent that

[7]In the cases of multiple clustered events, this procedure essentially boils down to estimating the joint effect of a cluster of events, which may be interpreted as a change in the MaP policy stance. We decide for the two-year exclusion window because all subsequent tests measure the effect of MaP changes during the two-year post-implementation period.

this assumption holds, any systematic movements in the excess growth rates following the implementation of MaP tools may be interpreted as being causally related to these MaPs.

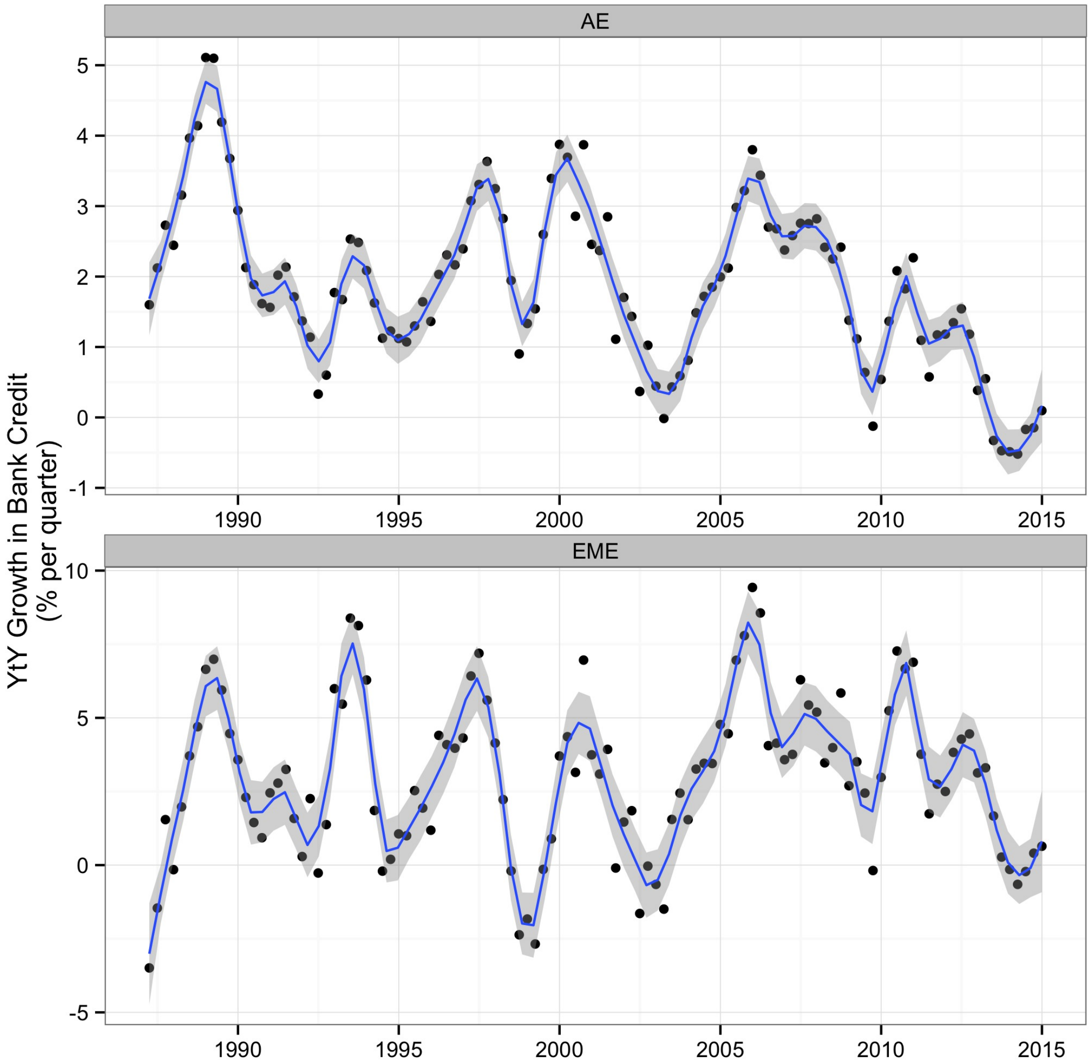
We study the effect of MaPs on the bank and non-bank sectors by examining the cumulative behavior of excessive growth rates starting three years prior to the implementation of a MaP and tracing its path until three years after. Specifically, for a time interval between α and β periods relative to MaP implementation, we compute Cumulative Excess Growth Rates (CEGR) as follows:

$$CEGR^s[a,b] = \sum_{i \in [a,b]} \phi_i^s \tag{5.7}$$

Under the null hypothesis of MaPs having no impact on credit or asset growth, CEGR is expected to be statistically indistinguishable from 0 both in periods before and after the implementation of MaPs. To the extent that banks' and non-banks' actions are influenced by MaPs, CEGRs are expected to systematically diverge from 0, and if the policies are anticipated before their actual implementation (and this triggers behavioral changes in financing patterns of banks and non-banks), the divergence is expected to occur already prior to the policy implementation date. We test the hypotheses related to CEGR by performing a series of Wald tests on the sums of coefficients in the specification.

5.4.2 Results

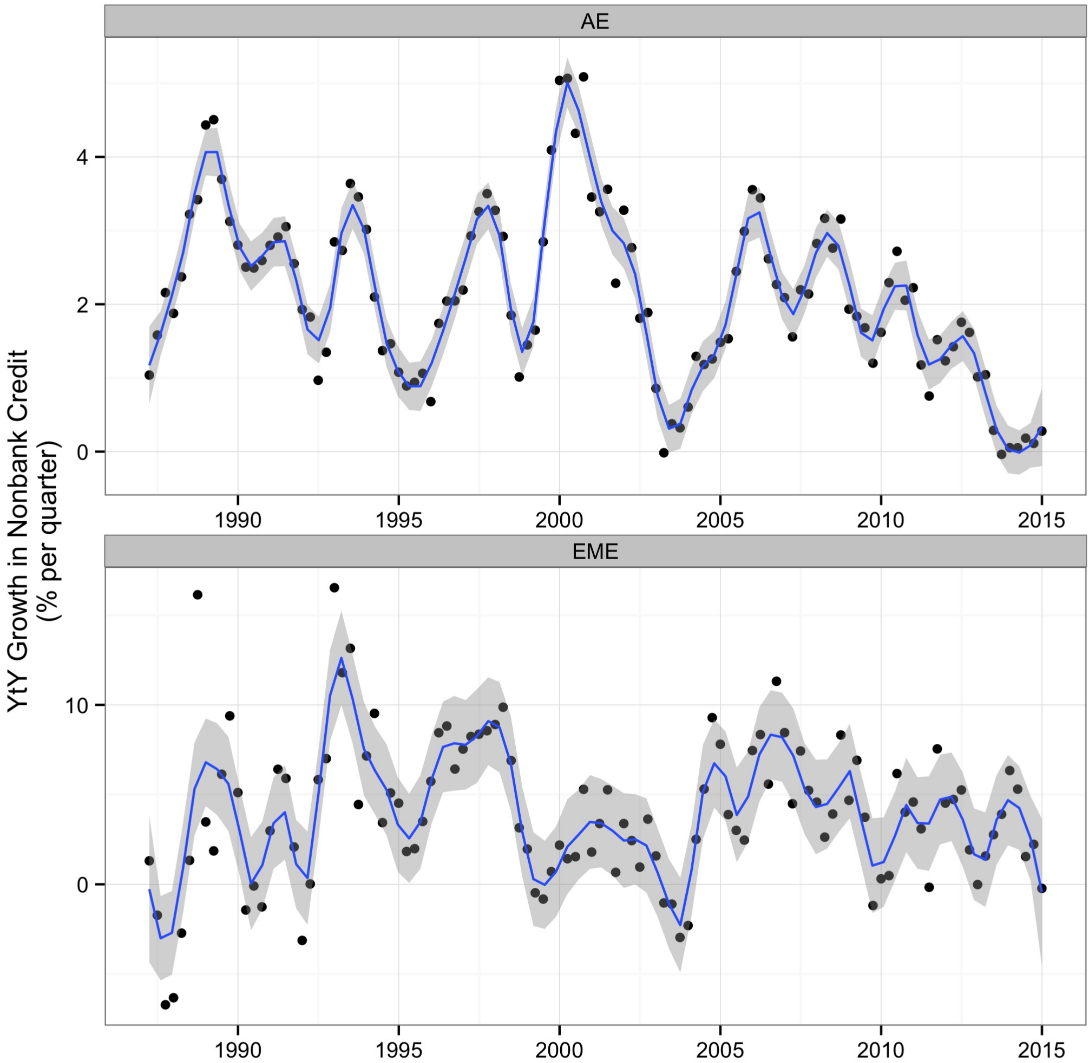
The coefficient estimates of the control variables in the expected growth rate specifications are reported in Table 5.5. Results are generally in line with the empirical literature on determinants of credit growth. For example, GDP growth shows the expected positive effect on both banking and non-bank credit, while a banking crisis has a negative impact on most sources of credit, except for investment funds growth and domestic private debt issuance. Again, this may reflect that a banking crisis prompts bank deleveraging (decline in credit supply by banks), and thus a shift by borrowers to capital markets. Comparing the explanatory power of the expected growth model across various sectors, we note that the macroeconomic fundamentals explain a much higher proportion of variation in the growth rates of bank credit than non-bank credit.



(a) Bank credit flows

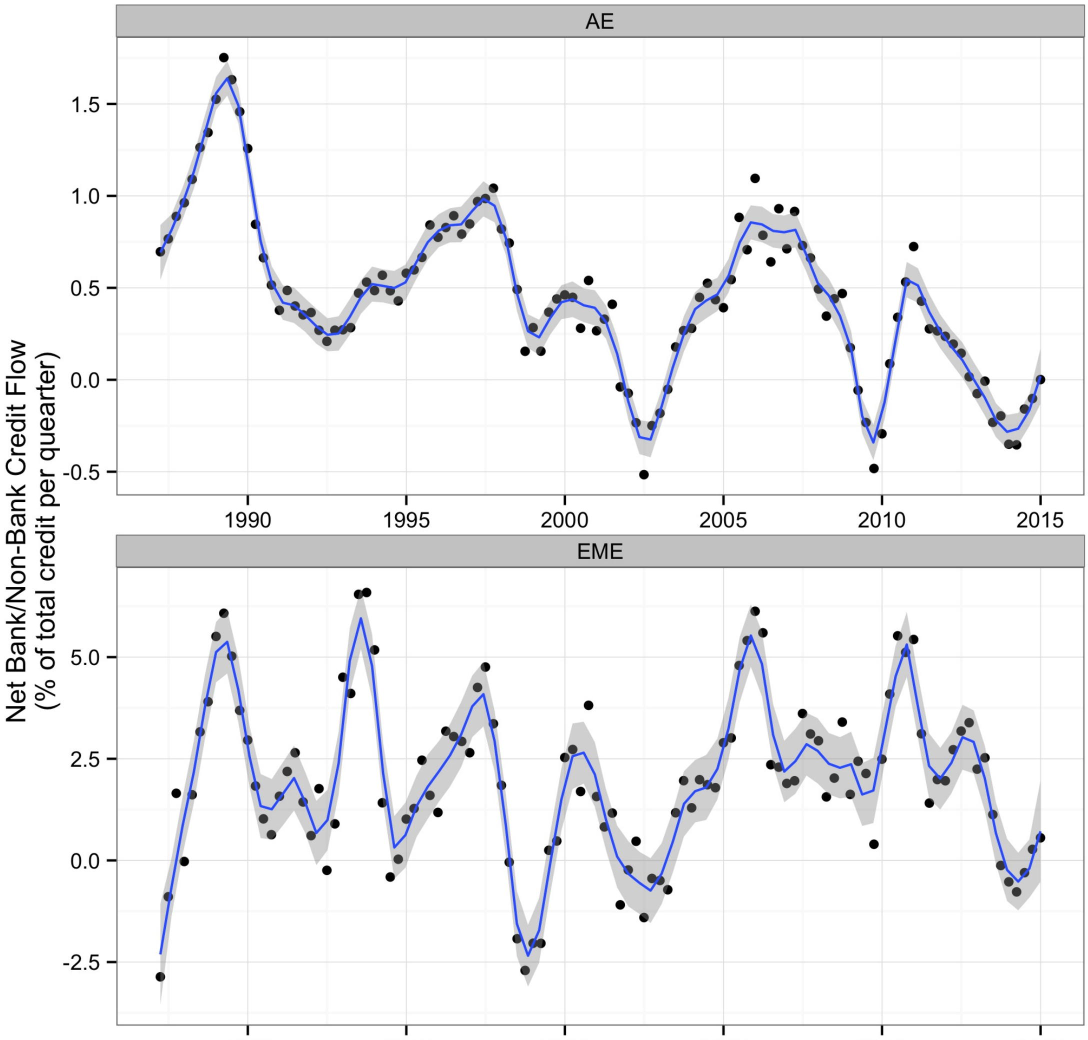
Figure 5.1 – Credit flows in advanced and emerging economies. The actual growth rates are represented by dots. The blue line is the LOESS fitted curve, with the smoothing parameter set to 0.1, and the shadowed region corresponds to the 95% confidence interval around the fitted values. Net sectoral credit flows are defined as:

$$100 * \frac{\frac{1}{4}[\Delta^{YtY}\text{Bank Credit}]_{ct} - \frac{1}{4}[\Delta^{YtY}\text{Non-Bank Credit}]_{ct}}{[\text{Total Credit}]_{c,t-4}}$$



(b) Non-bank credit flows

Figure 5.1 – Continued from previous page.



(c) Substitution between bank/non-bank credit flows

Figure 5.1 – Continued from previous page.

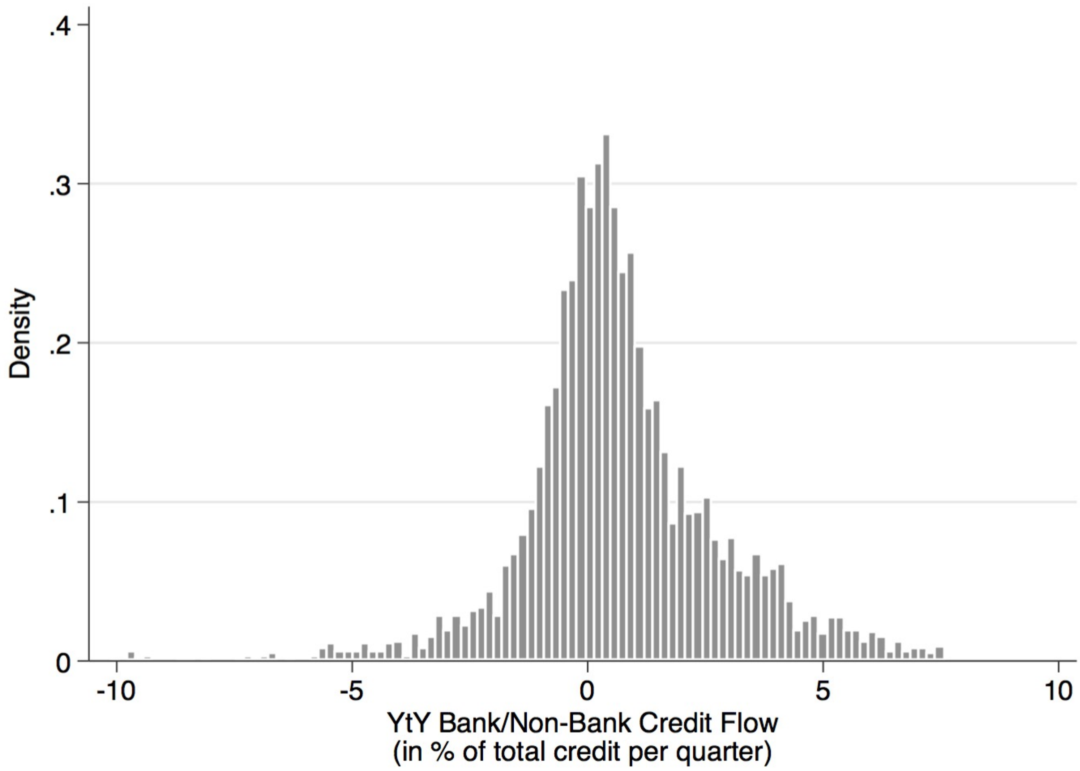


Figure 5.2 – Histogram of the substitution between bank/non-bank credit flows. The net-sectoral credit flow measure is defined as:

$$100 * \frac{\frac{1}{4}[\Delta^{YtY}\text{Bank Credit}]_{ct} - \frac{1}{4}[\Delta^{YtY}\text{Non-Bank Credit}]_{ct}}{[\text{Total Credit}]_{c,t-4}}$$

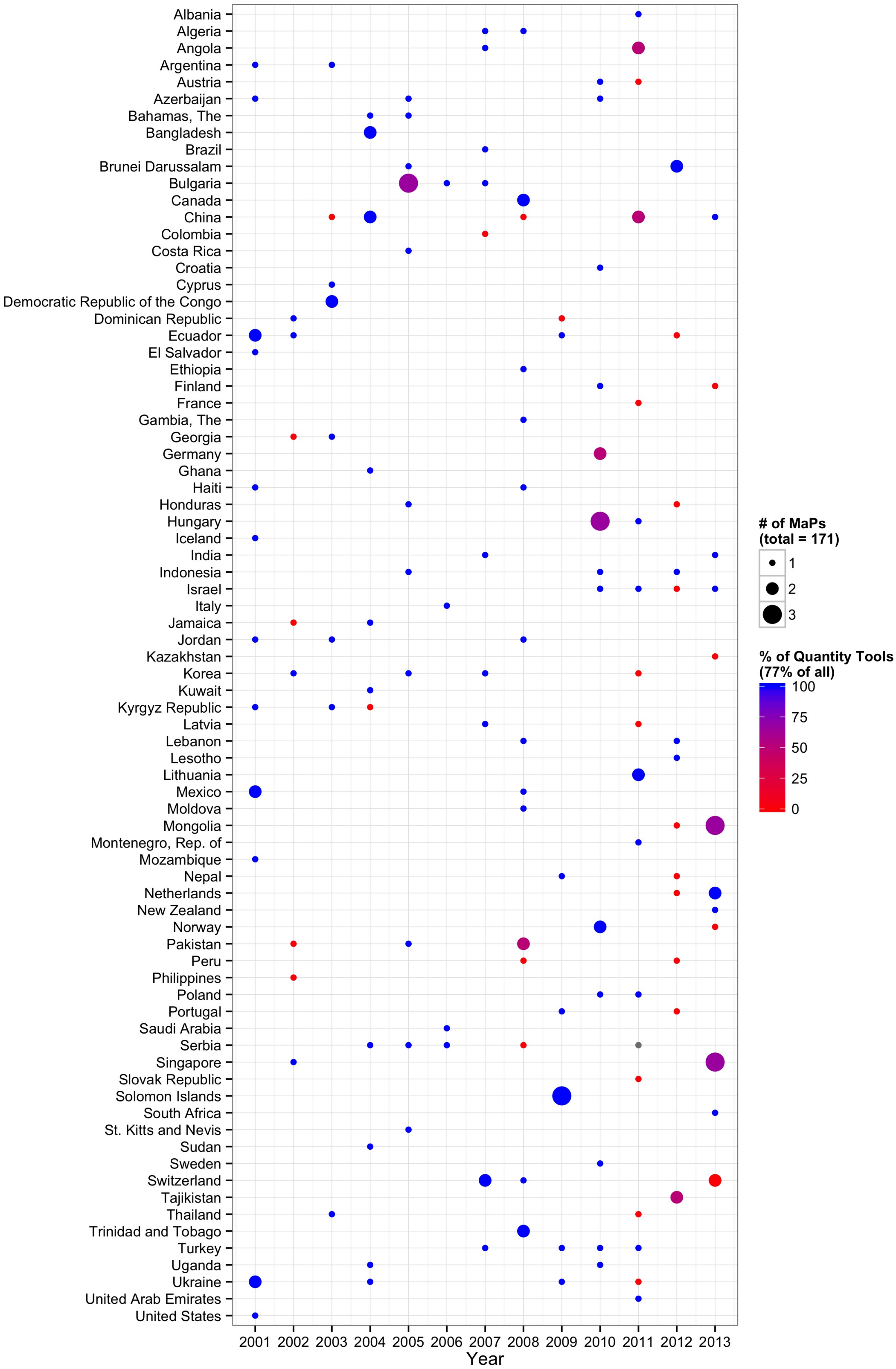


Figure 5.3 – Macroprudential policy measures.

Table 5.5 – Drivers of growth in credit, investment fund assets and domestic private debt securities

	Expected growth rate regressions				
	1-Year Growth in Bank Credit to Private Sector. Source: BIS (1)	1-Year Growth in Non-Bank Credit to Private Sector. Source: BIS (2)	1-Year Growth in Total Credit to Private Sector. (3)	1-Year Growth in Investment fund assets. Source: WB-GFDD (4)	Issuance of domestic private debt securities. Source: WB-GFDD (5)
Inflation (YtY % change in CPI)	0.25	0.18	0.17	0.05	0.94*
	(0.18)	(0.19)	(0.15)	(0.41)	(0.51)
YtY % Real GDP growth	0.85***	1.05***	0.76***	0.63***	0.31**
	(0.14)	(0.22)	(0.12)	(0.23)	(0.16)
Current account balance (% of GDP)	-0.01	-0.06	0.02	-0.89***	-0.54*
	(0.18)	(0.15)	(0.16)	(0.31)	(0.29)
General government net lending/borrowing (% of GDP)	0.62**	0.16	0.50**	0.20	0.72
	(0.28)	(0.30)	(0.23)	(0.40)	(0.50)
Equity inflows (% of GDP)	-0.11***	-0.11	-0.06	0.03	0.15
	(0.04)	(0.10)	(0.04)	(0.14)	(0.09)
Debt inflows (% of GDP)	0.03	-0.04	0.01	-0.04	0.00
	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)
CB Lending Rate (in %)	-0.20	0.29	-0.07	-0.16	-0.21
	(0.13)	(0.34)	(0.13)	(0.18)	(0.37)
YtY % Growth in CB Assets	-0.02**	0.01	-0.01	-0.05***	-0.03
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Log GDP per capita	-9.13***	4.51	-6.71***	-22.50**	0.19
	(2.64)	(4.15)	(2.11)	(9.03)	(6.31)
Banking crisis dummy	-5.73***	-5.68**	-6.19***	1.23	4.24***
	(1.73)	(2.36)	(1.65)	(4.57)	(1.34)
Constant	101.97***	-32.42	78.19***	239.85***	5.87
	(24.44)	(38.76)	(19.25)	(81.62)	(61.34)
R-squared	0.43	0.18	0.43	0.33	0.23
Observations	2433	2421	2425	3539	2852
Number of Countries	34	34	34	72	43

Notes:
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Overall effect of MaPs

Next, we analyze the behavior of the residuals from the expected growth rate regressions around the implementation of MaPs. Panels A-D in Figure 5.4 plot CEGRs around MaP events for bank, non-bank, and total credit flows, as well as for the net sectoral credit flows defined in Section 5.2. CEGRs are plotted over the period of 14 quarters before and 12 quarters after the implementation of MaPs, and for each figure we also report the result of Wald tests on CEGR during the two years prior to the implementation of a MaP and during the two years after implementation. The former tests for an anticipation effect of MaPs on bank and non-bank intermediation, whereas the latter tests for a post-implementation effect.

The trajectory of CEGR in the banking sector (Figure 5.4(a)) shows a statistically significant downward effect of MaPs on bank credit: during the two years following MaP implementation, the growth rate of bank credit is about 8pp below the baseline level, even after controlling for systemic banking crises and the general state of countries' economies. This finding is statistically significant with a p-value below 1%. The effect on the growth rate of bank credit begins to gather pace several quarters prior to MaP implementation, suggesting a pre-emptive slowing of credit supply by banks.

Non-bank credit growth exhibits almost the opposite pattern to bank credit growth (Figure 5.3(b)): during the two years after a MaP event it rises on average by about 10pp above baseline growth (from a lower level than bank credit). The effect is statistically significant at the 1% significance level. The post-implementation decline in bank credit and the contemporaneous rise in non-bank credit is consistent with the cross-sector substitution in credit found in the previous section.

Figure 5.4(c) shows the impact of MaP measures on the excess growth in total credit. In line with existing studies (e.g. Cerutti et al., forthcoming), we find that total credit declines during the two years after MaP implementation. Specifically, it declines by about 5pp below the baseline rate of growth, which indicates that the increase in non-bank credit does not fully compensate the contraction in bank credit.

Figure 5.4(d) shows the behavior of net sectoral credit flows around MaP measures and provides direct evidence of the substitution effect. Prior to MaP events the series is statistically indistinguishable from the baseline (p=0.31), whereas during two years after the event, the series moves about 4pp below the baseline (note that net credit flows are denominated in terms of total credit, see Section 5.2). The absence of a pre-existing trend strengthens the causal explanation of the negative post-event association between MaP events and net sectoral credit flows.

Effect of MaPs on alternative sources of non-bank finance

We further explore the dynamics of specific types of non-bank finance in Panels A and B of Figure 5.5, which plots CEGRs around MaP events for investment funds (Panel A) and domestic private debt issuance (Panel B). This aims to capture dynamics in market-based financing, which may become a viable source of finance for firms that find bank credit too expensive. In line with results on non-bank credit, investment fund assets exhibit strong positive growth around MaP implementation. The CEGR begins to pick up 6 quarters prior to the implementation, accelerates during the period 3 quarters before and 3 quarters after the policy measure, and decelerates thereafter. Over the two years following a measure, investment fund assets rise on average by 20pp above the baseline of no MaP policy (p-value=0.019). Similarly, domestic private debt issuance activity exhibits a strong positive growth up to 6 quarters following the MaP implementation (p=0.00). During the 2 years after the policy implementation, the domestic private debt issuance amounts to about 55pp above the baseline. The large magnitude of CEGRs is partially attributable to low initial levels of investment fund assets and private debt issuance in some of the countries in the sample (for example, investment funds in EMEs on average comprise only about 6% of GDP)[8].

Effect of MaPs across samples and tools

As in section 5.3, we also examine whether the effect of MaPs varies across different instruments and countries. Specifically, we re-do the event study for (1) AEs and EMEs, (2) quantity and price-based measures, and (3) the combination of the two. As before, we report event study results for bank credit (Figure 5.6), non-bank credit (Figure 5.7), total credit (Figure 5.8), and net sectoral flows (Figure 5.9). Table 5.6 summarizes the results from Figures 5.6-5.9 by listing the effects for 2-year post-event windows for various samples of countries and tools.

The intended effect of MaP events on bank credit is statistically highly significant and generally stronger in EMEs than in AEs: in AEs bank credit slows by 3.2pp below

[8]Example: suppose that an initial level of bank credit in country A is 10 local currency units (LCU), and that of a non-bank sources is 1 LCU. Next, suppose that an implementation of a policy results in a shift in credit provision from banks towards non-bank sources in the amount of 1 LCU. The post-policy-event credit provision is then 9 LCU for banks and 2 LCU for non-banks. Assuming that during the same period bank and non-bank credit in countries without policy intervention grew by 0%, the post-event CEGR in country A is -10% for banks and +100% for non-banks.

Table 5.6 – Summary of event study results

Panel A: Effects on bank and total credit

	Post-implementation effect of MaP					
	All Instruments		Quantity Measures		Price Measures	
	Bank Credit	Total Credit	Bank Credit	Total Credit	Bank Credit	Total Credit
All	-7.70***	-4.90***	-8.70***	-4.10***	1.70	1.20
AEs	-3.20**	-1.60	-6.60***	-1.50	2.00	2.10
EMEs	-9.90***	-6.50***	-10.40***	-6.90***	1.50	-2.80

Panel B: Cross-sector credit substitution.

	All Instruments	Quantity Measures	Price Measures
All	-4.30***	-5.20***	2.30
AEs	-4.10***	-4.60***	-1.20
EMEs	-6.20***	-6.50***	1.10

Notes:
[1] Panel A reports the effects of MaP events on the average cumulative credit growth rates during the 2-year period following the implementation of macroprudential policies. Growth rates are adjusted for the baseline rates of growth implied by countries' macroeconomic fundamentals.
[2] Panel B reports the effects of MaP events on the net sectoral credit flow cumulated over the 2-year period following the implementation of macroprudential policies. The measure is defined as follows:

$$[Quarterly\text{Net Sectoral Credit Flow}]_{ct} = 100 * \frac{\frac{1}{4}[\Delta^{YtY}\text{Bank Credit}]_{ct} - \frac{1}{4}[\Delta^{YtY}\text{Non-Bank Credit}]_{ct}}{[\text{Total Credit}]_{c,t-4}}$$

[3] Emerging country group consists of the following countries: Brazil, China, Hungary, Indonesia, India, Mexico, Malaysia, Thailand, Turkey, and South Africa. Advanced country group consists of: Australia, Austria, Belgium, Canada, Switzerland, Czech Republic, Germany, Denmark, Spain, Finland, France, United Kingdom, Greece, Hong Kong, Ireland, Italy, Japan, Luxembourg, Netherlands, Norway, Poland, Portugal, Russia, Saudi Arabia, Singapore, Sweden, and the USA.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

the baseline, whereas in EMEs it slows by 9.9pp. Further distinguishing between quantity constraints on credit and price-based measures shows that most of the decline in bank credit in both AEs and EME comes from quantity-based constraints: in AEs (EMEs), quantity-based measures lead to a 6.6pp (10.4pp) contraction below the baseline during the two years after the event. This confirms the intuition that quantity limits are more binding than measures that increase the cost of credit. Moreover, bank credit growth is above the baseline before the implementation of quantity-based measures. This suggests that authorities respond to periods of high credit growth by implementing stronger constraints. Price-based measures, on the other hand, have no statistically distinguishable impact on banks in AEs or EMEs.

Next, turning to the effects of MaP measures on total credit, the effect is negative both in AEs and EMEs, but statistically significant only in EMEs. The difference in the effects on bank credit and total credit is larger in AEs, especially for quantity constraints. A possible explanation is that substitution effects are larger in countries with more developed financial systems, which offer a broader range of opportunities for substitution between forms of finance (as indicated in Table 5.1, non-bank credit is much larger in AEs than in EMEs).

Table 5.6B summarizes the event-study results for net sectoral credit flows across countries and MaPs. On average, the impact of MaPs is statistically negative in both AEs and EMEs, but only in the case of quantity-based measures.

In summary, the evidence presented in this section shows that MaP measures lead to:

- A reduction in bank credit flows. This is the intended effect of MaPs.
- An increase in non-bank credit flows. This confirms the existence of substitution effects and the relevance of the boundary problem for MaPs.
- A reduction in total credit flows. This finding indicates that substitution effects do not fully compensate the impact on bank credit. In fact, the residual effect on total credit is still relatively large – total credit contracts by a cumulative 5pp below the baseline during the 2 years after a MaP event.
- Stronger substitution effects in AEs than in EMEs. This may reflect the opportunities provided by a more developed non-bank sector.
- Stronger effects when the measures directly constrain credit. This is in line with the intuition that the tightest constraints are the most binding and thus also lead to more substitution.
- A reduction in net sectoral flows. This is consistent with the substitution effect of macroprudential policies.

5.5 Robustness Checks

We perform several tests to check the robustness of our results.

5.5.1 Placebo Tests

The credibility of our empirical design in sections 5.3 and 5.4 is assessed with a series of placebo tests. Placebo testing involves generating a series of 'fake' macroprudential policy shocks, and then testing the behavior of credit measures around these shocks.

Since the shocks are generated at random, one expects to observe no abnormal movements in credit outcomes either prior or after the shocks. The presence of such movements would suggest the existence of unexplained trends in the data, and would thus call for changes in the identification methodology.

We proceed along the following steps:

- For each country-year observation in the original Cerutti et al. (2015) dataset we draw a Bernoulli distributed indicator to simulate the placebo dates of policy changes. We repeat this process for each of the 12 MaP tools in the original database. We match the distribution of the simulated and the actual MaP events by setting the Bernoulli probability parameter to the relative frequency of the corresponding tool deployments in the original dataset.

- Using the simulated MaP we compute the aggregate MaP indices, which, in turn, are used to derive MaP event indicators. Figure 5.10 provides an overview of the simulated MaP measures. As in Figure 5.3, circles mark the periods of MaP implementation, the circle size corresponds to the number of policies implemented by a country in that year and the color of circles indicates the percentage of quantity-based MaPs.

- We repeat the event study in section 5.4, using the simulated set of MaP indicators in Figure 5.10.

Table 5.7 reports results of the event study with the simulated MaP events. Impact window effects are in most cases statistically indistinguishable from zero, which indicates that our results in the previous sections are not driven by spurious trends in the data.

5.5.2 Effect of MaP Events Prior to and During the Global Financial Crisis

A large fraction of MaPs were implemented during and after the GFC. A concern about the effects found in the previous sections is that they capture not only MaPs but also a host of other factors that took place during that time. While our previous analysis tries to control for these factors by explicitly accounting for the presence of banking crises, changes in monetary policy, and other macroeconomic fundamentals, there may be remaining omitted factors that affect credit to the private sector and are also correlated with the timing of MaP activations.

Table 5.7 – Event study using placebo event dataset. Summary of results.

Panel A: Effects on bank and total credit

	Post-implementation effect of MaP					
	All Instruments		Quantity Measures		Price Measures	
	Bank Credit	Total Credit	Bank Credit	Total Credit	Bank Credit	Total Credit
All	0.90	1.10	-0.80	0.10	1.60	-0.20
AEs	2.00	1.80	-0.20	0.30	2.90	-0.90
EMEs	-4.50	-6.00*	-4.20	-6.60	-7.90	-8.40

Panel B: Cross-sector credit substitution.

	All Instruments	Quantity Measures	Price Measures
All	-0.10	-1.20	4.40*
AEs	1.50	0.20	5.40*
EMEs	-3.80	-6.20	0.70

Notes:
[1] Panel A reports the effects of MaP events on the average cumulative credit growth rates during the 2-year period following the implementation of macroprudential policies. Growth rates are adjusted for the baseline rates of growth implied by countries' macroeconomic fundamentals.
[2] Panel B reports the effects of MaP events on the net sectoral credit flow cumulated over the 2-year period following the implementation of macroprudential policies. The measure is defined as follows:

$$[\mathit{Quarterly}\text{Net Sectoral Credit Flow}]_{ct} \quad = 100 * \frac{\frac{1}{4}[\Delta^{YtY}\text{Bank Credit}]_{ct} - \frac{1}{4}[\Delta^{YtY}\text{Non-Bank Credit}]_{ct}}{[\text{Total Credit}]_{c,t-4}}$$

[3] Emerging country group consists of the following countries: Brazil, China, Hungary, Indonesia, India, Mexico, Malaysia, Thailand, Turkey, and South Africa. Advanced country group consists of: Australia, Austria, Belgium, Canada, Switzerland, Czech Republic, Germany, Denmark, Spain, Finland, France, United Kingdom, Greece, Hong Kong, Ireland, Italy, Japan, Luxembourg, Netherlands, Norway, Poland, Portugal, Russia, Saudi Arabia, Singapore, Sweden, and the USA.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

We thus examine the effectiveness of macroprudential policies before and after the onset of the GFC. Specifically, we repeat the event studies in section 5.4 for the periods before and after the onset of the GFC, which we take to be the third quarter of 2007. Results of the exercise are reported in Table 5.8. Because of the lack of price-based MaP events prior to the GFC, we only report the results for the quantity-based measures for the pre-GFC period.

In line with our previous analysis, quantity-based tools during the pre-GFC era reduce bank credit in both AEs and EMEs. Furthermore, cross-sector substitution towards non-banks is statistically and economically significant in both groups of countries, both before and after the GFC. Interestingly, in AEs, the cross-sector substitution associated with the implementation of quantity-based measures is larger during the pre-GFC era.

Table 5.8 – Event study results before and after 2007Q3

Panel A: Effects on bank and total credit

Effects prior to 2007Q3

	Post-implementation effect of MaP					
	All Instruments		Quantity Measures		Price Measures	
	Bank Credit	Total Credit	Bank Credit	Total Credit	Bank Credit	Total Credit
All	-8.80***	-4.70**	-8.80***	-4.70**	NA	NA
AEs	-7.30**	-6.50*	-7.30**	-6.50*	NA	NA
EMEs	-9.20**	-3.30	-9.20**	-3.30	NA	NA

Effects after 2007Q3

	Post-implementation effect of MaP					
	All Instruments		Quantity Measures		Price Measures	
	Bank Credit	Total Credit	Bank Credit	Total Credit	Bank Credit	Total Credit
All	-3.70**	-1.70	-4.80***	-2.80**	4.10*	5.80**
AEs	-1.30*	0.40	-1.60*	0.40	1.00	2.20
EMEs	-9.60***	-7.50***	-10.50***	-8.60***	3.50	5.80*

Panel B: Cross-sector credit substitution.

Effects prior to 2007Q3

	All Instruments	Quantity Measures	Price Measures
All	-6.10***	-6.10***	NA
AEs	-5.70***	-5.70***	NA
EMEs	-6.00***	-6.00***	NA

Effects after 2007Q3

	All Instruments	Quantity Measures	Price Measures
All	-2.60***	-4.20***	3.10
AEs	-1.90**	-2.70**	0.10
EMEs	-5.10***	-6.50***	2.50

Notes:

[1] Panel A reports the effects of MaP events on the average cumulative credit growth rates during the 2-year period following the implementation of macroprudential policies. Growth rates are adjusted for the baseline rates of growth implied by countries' macroeconomic fundamentals.

[2] Panel B reports the effects of MaP events on the net sectoral credit flow cumulated over the 2-year period following the implementation of macroprudential policies. The measure is defined as follows:

$$[Quarterly\text{Net Sectoral Credit Flow}]_{ct} \;= 100{*}\frac{\frac{1}{4}[\Delta^{YtY}\text{Bank Credit}]_{ct} - \frac{1}{4}[\Delta^{YtY}\text{Non-Bank Credit}]_{ct}}{[\text{Total Credit}]_{c,t-4}}$$

[3] Emerging country group consists of the following countries: Brazil, China, Hungary, Indonesia, India, Mexico, Malaysia, Thailand, Turkey, and South Africa. Advanced country group consists of: Australia, Austria, Belgium, Canada, Switzerland, Czech Republic, Germany, Denmark, Spain, Finland, France, United Kingdom, Greece, Hong Kong, Ireland, Italy, Japan, Luxembourg, Netherlands, Norway, Poland, Portugal, Russia, Saudi Arabia, Singapore, Sweden, and the USA.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

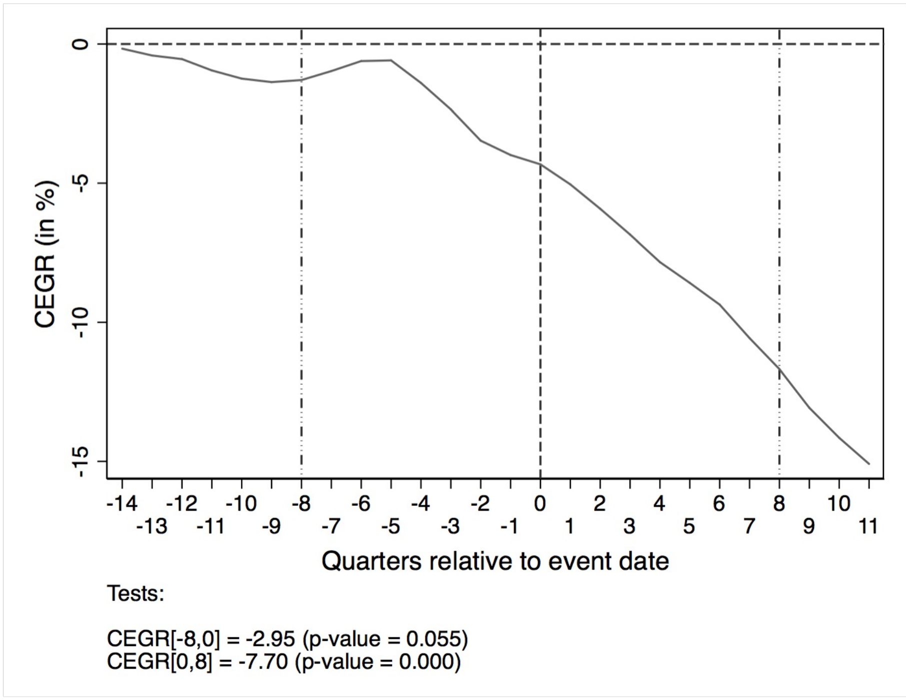
5.6 Conclusions

Macroprudential policy is being implemented both to boost the resilience of the financial sector and to dampen the financial cycle, in advanced and emerging market economies alike. This paper examines its effectiveness. Macroprudential policies are found to reduce bank credit across countries: on average, bank credit falls by almost 8 percentage points in the 2 years following macroprudential policy measures relative to the counterfactual of no measures. This is consistent with the intention of policy makers to limit bank credit growth and thereby reduce the likelihood and impact of systemic banking stress. Yet, second, we establish that these measures coincide with substitution effects, as credit provision shifts from banks towards non-banks. Cross-sector substitution is particularly pronounced following the implementation of quantity-based measures aimed at banks, and in advanced economies and bank-based financial systems. The growth of investment funds and of capital market debt issuance following macroprudential measures applied to banks illustrates how these measures are offset by new forms of credit growth outside the banking sector.

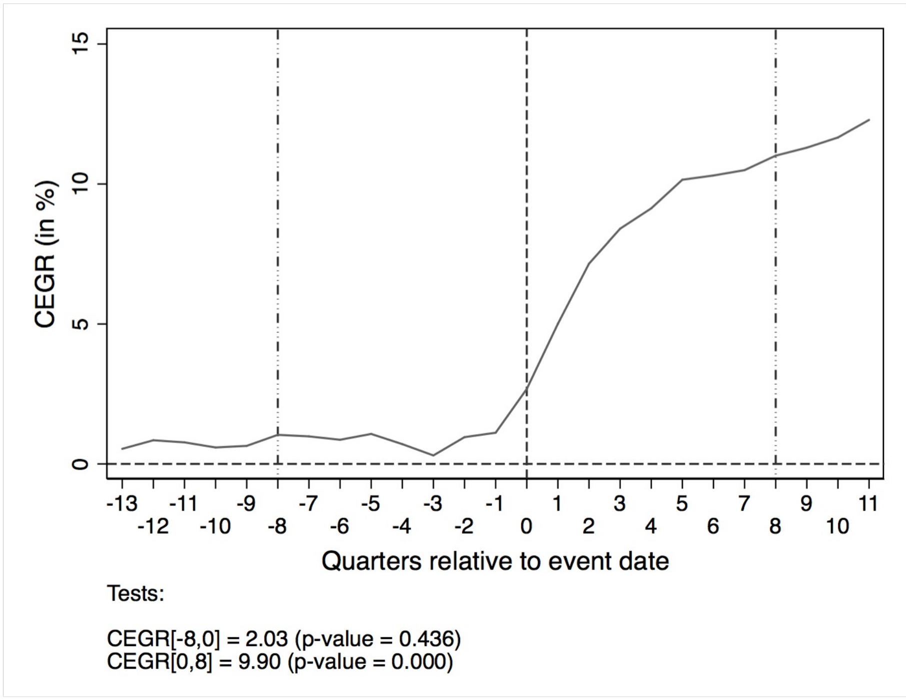
A number of factors reduce concerns about the cross-sector substitution effects of macroprudential policies. In particular, the non-bank financial sector is generally less leveraged, has less liquidity risks and is separated from systemic functions related to the payments infrastructure. Moreover, it does not benefit from explicit public sector safety nets, such as deposit insurance and central bank liquidity support. In this light, policymakers may welcome a shift to market-based financing, which can function as a “spare tire” in the supply of credit in times of systemic banking crises (IMF, 2015). These considerations motivate the plans for the creation of a European Capital Markets Union.

Yet new systemic risks may emerge. When an expanding credit bubble shifts from banks to financial markets, and households or corporates continue to accumulate debt, macroeconomic vulnerabilities rise and may still prove costly, even if the debt is owed to investment funds and to capital market creditors rather than banks. Similarly, when investment funds purchase illiquid debt securities while promising liquidity to end investors, debt markets become vulnerable to refinancing risks and sudden price shocks. Moreover, when the non-bank financial sector is interconnected with the formal banking sector (e.g. through credit lines, participation in banks’ debt issuances, or ownership links), shocks in the former reverberate through the latter.

For macroprudential policymakers, there is thus work to be done. While macroprudential policy mitigates banking sector risks, there is a need to extend its scope beyond banking. The focus should be on systemic risks, and not on substitution per se. In some cases, activity-based instruments, which target the risk of an activity regardless of where it is conducted, can address risks more effectively. In other cases, instruments similar to those applied to banks can be applied to non-bank institutions. For example, margining requirements for securities financing transactions may perform a similar function as leverage requirements for banks and LTV limits for mortgages (Schoenmaker and Wierts, 2015). Similarly, limits on leverage and liquidity transformation (where not yet in place) can ensure that investment funds engaging in bank-like activities and taking on bank-like risks face comparable requirements.

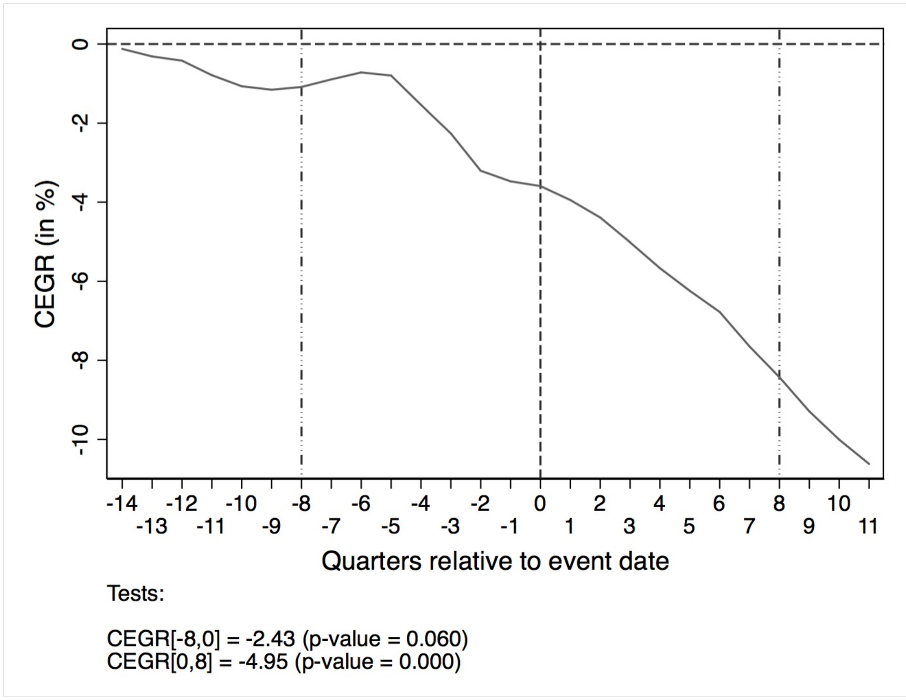


(a) Bank credit

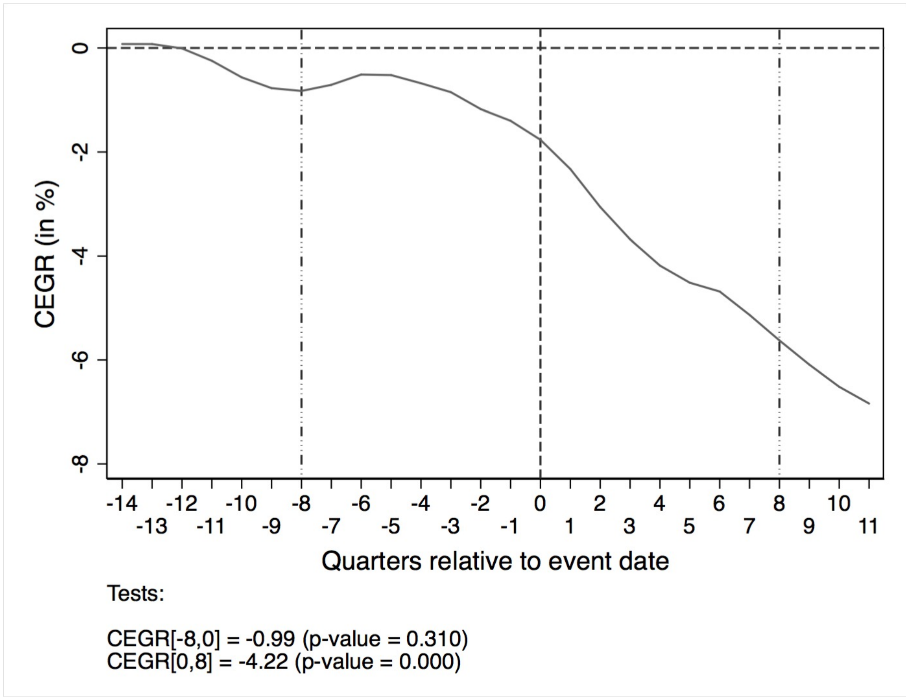


(b) Non-bank credit

Figure 5.4 – Cumulative excess credit growth rates around macroprudential measures.

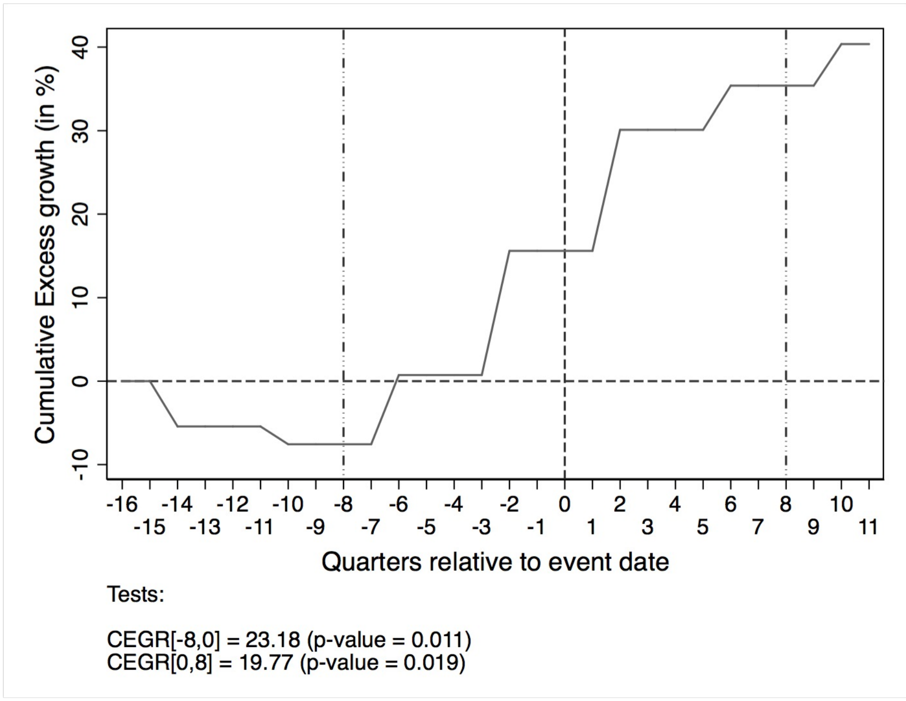


(c) Total credit

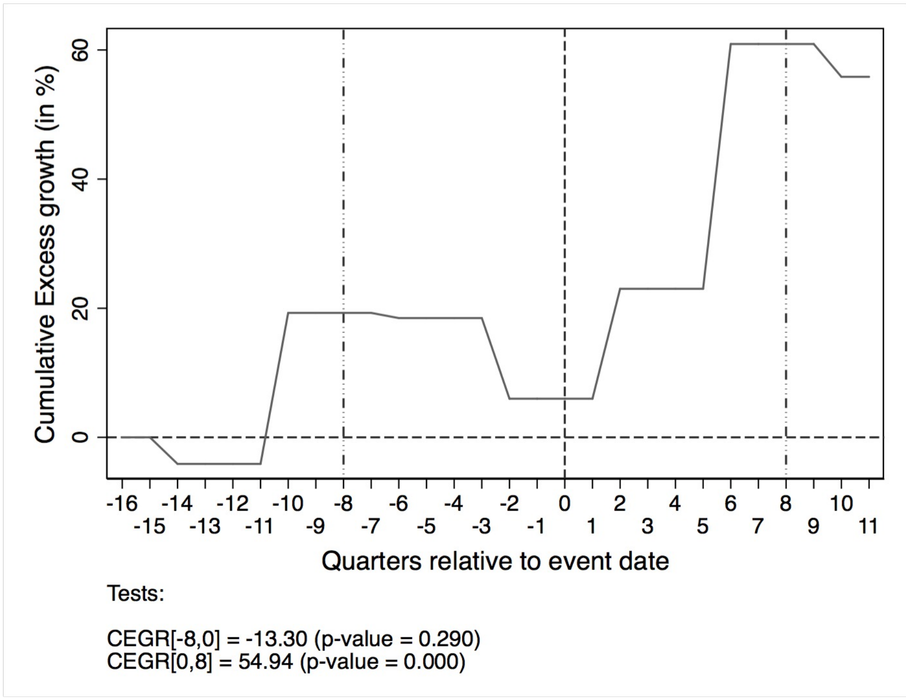


(d) Net sectoral credit flow

Figure 5.4 – Continued from previous page.

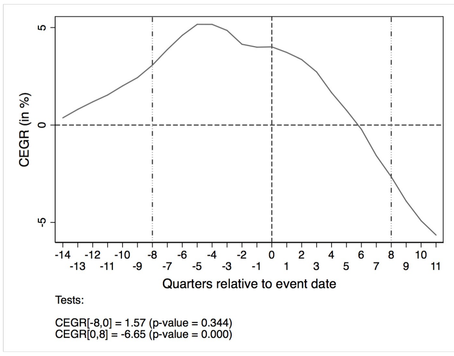


(a) Investment Fund Asset Growth

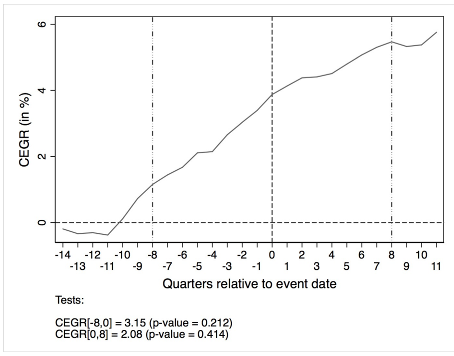


(b) Domestic Private Debt Issuance

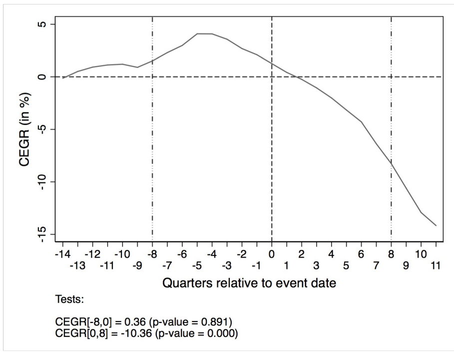
Figure 5.5 – Cumulative excess growth of non-bank FIs' assets around macroprudential measures.



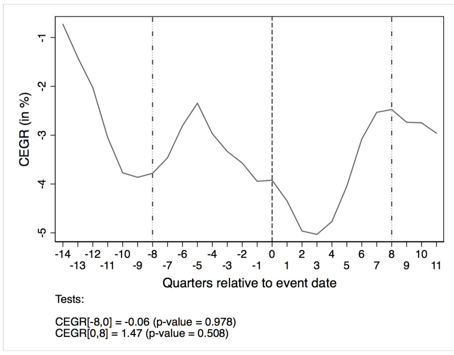
(a) AEs - Quantity Measures



(b) AEs - Price Measures

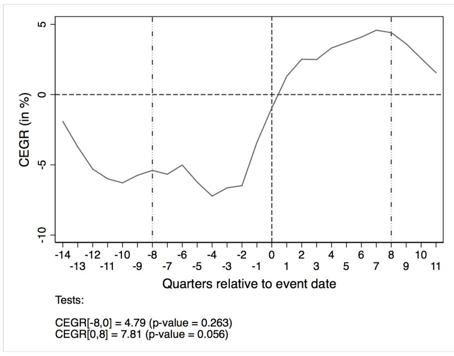


(c) EMEs - Quantity Measures

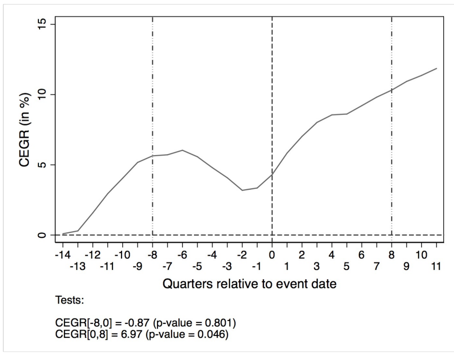


(d) EMEs - Price Measures

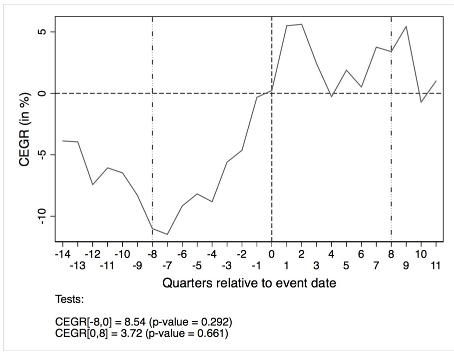
Figure 5.6 – Impact of MaP measures on **bank credit**.



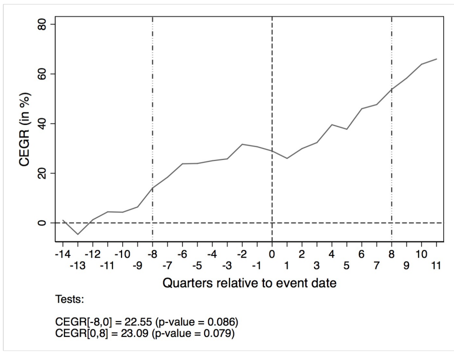
(a) AEs - Quantity Measures



(b) AEs - Price Measures

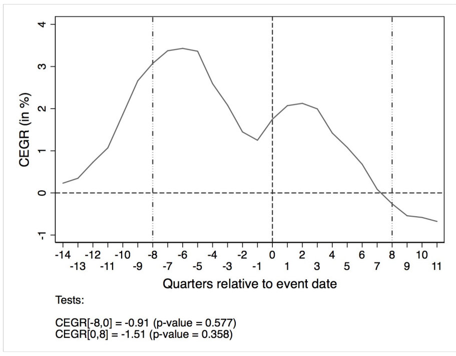


(c) EMEs - Quantity Measures

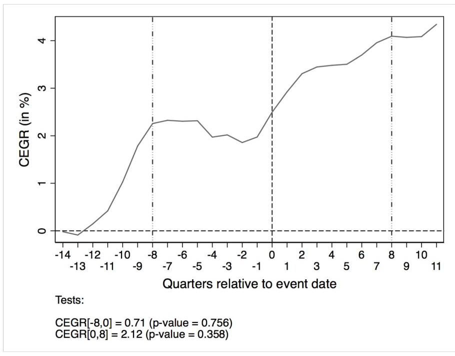


(d) EMEs - Price Measures

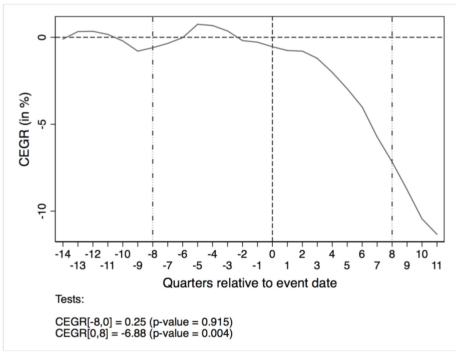
Figure 5.7 – Impact of MaP measures on **non-bank credit**.



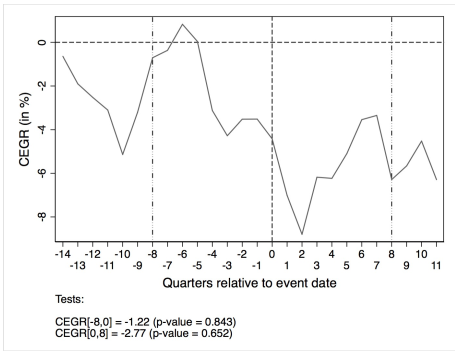
(a) AEs - Quantity Measures



(b) AEs - Price Measures

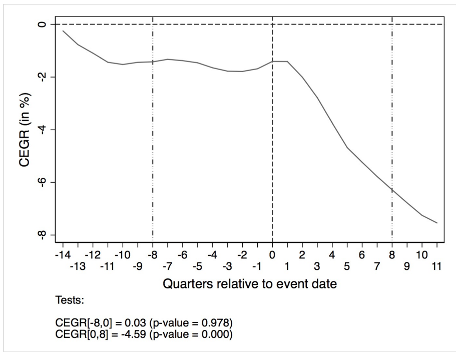


(c) EMEs - Quantity Measures

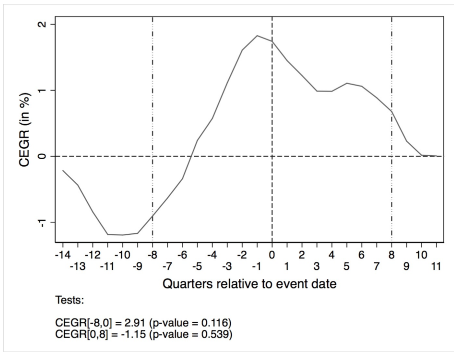


(d) EMEs - Price Measures

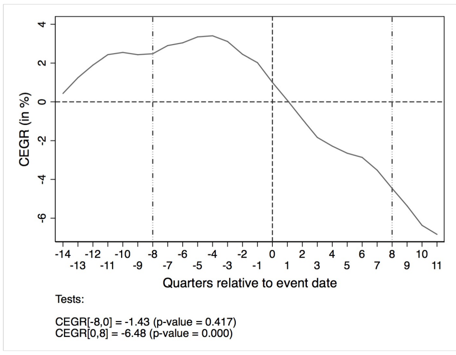
Figure 5.8 – Impact of MaP measures on **total credit**.



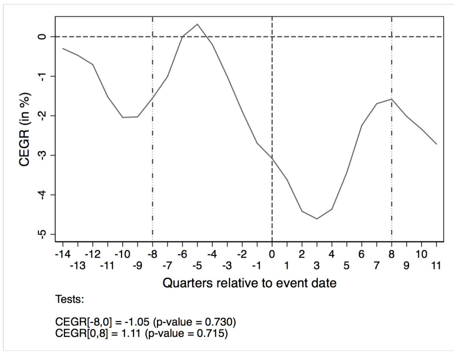
(a) AEs - Quantity Measures



(b) AEs - Price Measures



(c) EMEs - Quantity Measures



(d) EMEs - Price Measures

Figure 5.9 – Impact of MaP measures on **net sectoral credit flow**.

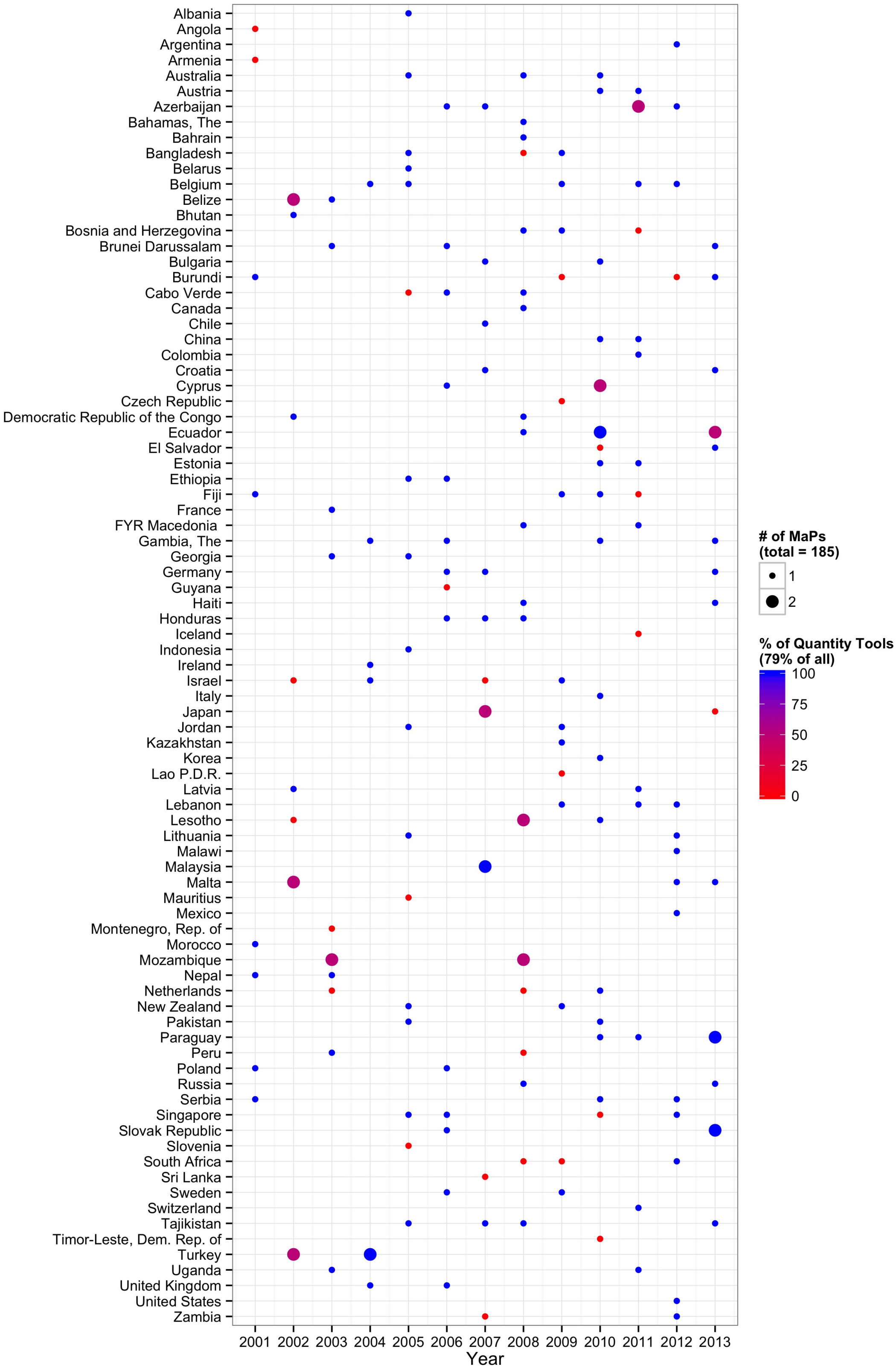


Figure 5.10 – Simulated macroprudential policy measures used in the placebo tests.

Appendix

5.A Importance of Cross-Border Claims in the Total Credit Measure from the BIS Database on Private Non-Financial Sector Credit

One of the issues with the BIS database on Private Non-Financial Sector Credit - at least in the context of analyzing cross-sector substitution - is that the Total Credit series, which we use to derive the non-bank credit series, also contains direct cross-border lending by foreign banks[9]. This may be problematic because the substitution effects that we identify in this chapter may be attributed not only to cross-sector substitution but also to cross-border substitution towards foreign banks. While both effects belong to the class of so-called "waterbed effects", where credit provision shifts from more to less regulated entities – either within or across borders, policy implications of the two types of events are different.

Validity of our "cross-sector substitution" interpretation of results hinges on the extent to which our non-bank credit measure (NBC), defined as the difference between total credit (TC) and domestic bank credit (BC), also captures the direct cross-border lending to the domestic non-financial private sector by foreign banks (henceforth CB_NFPS).

Upon a close reading of the BIS documentation[10], one can learn that:

1. By construction, the TC (and, by derivation, the NBC) measure does include CB_NFPS in some countries.

2. The BIS cross-border credit database (BIS-CBDB) may allow us to adjust the NB measure by accounting for cross-border exposures. Whether the adjustment is successful depends on how well the exposure measures in BIS-CBDB capture the CB_NFPS. As stated in the BIS documentation, the BIS-CBDB does not provide CB_NFPS directly, but rather the cross-border credit exposure to non-banks (henceforth CB_NB), which includes (1) cross-border credit exposure to non-bank financial institutions (henceforth CB_NBFI) and (2) the CB_NFPS. Succinctly: CB_NB (observable) = CB_NFPS (unobservable) + CB_NBFI (unobservable).

[9] We thank Win Monroe (IMF) for identifying this issue.
[10] The documentation is available at: `http://www.bis.org/statistics/totcredit.htm`.

How important are the CB_NFPS exposures in our NBC measure? While the CB_NFPS measure is not available at the country level, the BIS does report the aggregate CB_NFPS for all BIS reporting members over the period 2013Q4-2015Q3[11]. Table 5.9 reports the CB_NFPS as a percentage of NBC for the aggregate of all BIS reporting members. The CB_NFPS amounts to less than 5% of NBC on average and thus does not seem to be a major driving component in the non-bank credit measure.

Table 5.9 – Cross-border credit to the non-financial sector (CB_NFPS) as a percentage of the total non-bank credit to the non-financial private sector (NBC)

Series	2014Q1	2014Q2	2014Q3	2014Q4	2015Q1	2015Q2	2015Q3
CB_NFPS (% of NBC)[1]	3.25%	3.25%	3.14%	4.22%	4.17%	4.25%	4.16%

[1] Series constructed as follows (BIS time series codes): 100*[Q:S:C:G:TO1:A:5J:A:5A:P:5J:N] / ([Q:5A:P:A:M:USD:A] - [Q:5A:P:B:M:USD:A])

The second question is this: is it desirable to adjust the NBC for CB_NFPS? As mentioned above, CB_NFPS is not available at the country level. The second best approach might be to approximate the CB_NFPS with CB_NB, which is available at the country level. Whether or not this approach is sensible depends on the extent to which CB_NB captures CB_NFPS. Table 5.10 reports CB_NFPS as a percentage of CB_NB, again for the aggregate of all BIS reporting countries.

Table 5.10 – Cross-border credit to the non-financial sector (CB_NFPS) as a percentage of the total non-bank credit to the non-financial private sector (NBC)

Series	2014Q1	2014Q2	2014Q3	2014Q4	2015Q1	2015Q2	2015Q3
CB_NFPS (% of CB_NB)[1]	18.97%	19.03%	18.25%	25.32%	24.48%	25.38%	24.85%

[1] Series constructed as follows (BIS time series codes): 100*[Q:S:C:G:TO1:A:5J:A:5A:N:5J:N] / [Q:S:C:G:TO1:A:5J:A:5A:P:5J:N]

Table 5.10 shows that more than three quarters of CB_NB consists of cross-border lending to other non-bank financial institutions (CB_NBFI). Adjusting NBC with

[11] Database name: Locational Banking Statistics. Series name: Q:S:C:G:TO1:A:5J:A:5A:P:5J:N. For further information see: `http://www.bis.org/statistics/bankstats.htm`

CB_NB may thus be even counter-productive, because it would essentially involve adjusting NBC with components it does not include in the first place.

While the concern about the NBC capturing cross-border exposures is valid, the evidence presented above suggests that the importance of cross-border credit is relatively minor (it amounts to less than 5% of NBC for the entire sample). We thus argue that the comparison of BC and NBC flows can give useful insight on the provision of credit across sectors.

CHAPTER 6

Conclusions

This thesis aims to contribute to several important and, at times, heated debates that have captured interest of academics and policy makers after the GFC. It is structured as a collection of four independent empirical essays, which revolve around two overarching themes. These are: (1) the quality of information production in financial markets (Chapters 1-3) and (2) the motivations and consequences of the financial sector policies and regulations deployed in response to the GFC (Chapters 3-4).

Chapter 2 studies the intra-industry informational transfers (IIIT), defined as the phenomenon whereby the firm-specific event of one firm in an industry can be used to make inference about the asset pricing distribution of the firm's industry-related peers. We study the IIIT induced by rating signals in the context of the markets for corporate credit risk. In particular, we study the intra-industry CDS spread responses to credit rating announcements made by S&P, Moody's, and Fitch between January 2003 and March 2011. We find statistically and economically significant industry spread responses to the announcements made by S&P, and only marginally significant and insignificant industry spread responses to the rating signals of Moody's and Fitch, respectively. This suggests that S&P announcements contain the largest component of the industry-wide information. In the case of S&P, we observe strong evidence in favor of contagious IIIT, implying that on the day of announcement the industry abnormal spreads tend to move in the same direction as the event-firm spreads. This finding holds across all four types of rating events, and in particular for the cases in which the event-firm spread reaction has its predicted sign (positive (negative) spread change in the case of negative (positive) rating news). The magnitude of the industry peer reaction (to S&P announcements) is found to be about 6% of the event-firm abnormal spread change. Stratification and multivariate regression analyses reveal a rich pattern of IIIT behavior across several event-firm, event, and industry characteristics. For negative rating events, contagious IIIT effects tend to be stronger when event-companies: (a) are relatively large (only in the case of downgrades), (b) come from industries with large industry peers, (c) have high degree of cash-flow similarity with their industry peers, (d) are highly leveraged, (e) have higher than industry-average credit rating before the event, and (f) come from relatively credit-worthy industries. For positive rating events, the contagious IIIT effects tend to increase with: (a) industry-peer cash flow similarity, and (b) degree of financial distress, characterized by below-average event-firm credit quality and low average industry credit quality.

Chapter 3 examines the nexus between reporting discretion and the information content of banks' public disclosures in the prediction of bank distress using an international sample of banks from 15 Western European countries and the U.S. during the financial crisis of 2007-12. We assemble an exhaustive and unique set of bank distress events, and model bank distress as a function of accounting-based fundamentals, while controlling for country-year fixed effects, and the type of resolution in the distressed entity. The analysis of our bank distress models reveals a substantial cross-country variation in the ability of accounting fundamentals to discriminate between distressed and non-distressed banks within countries. We examine the extent to which the variation in informativeness and accuracy of accounting fundamentals is explained by proxies of country-specific bank disclosure requirements and the enforcement thereof. We show that the association between accounting fundamentals and bank distress is attenuated in jurisdictions with relatively lax bank disclosure laws and their implementation. Accounting ratios, whose information value is the most sensitive to the quality of regulatory disclosure include regulatory capital ratios, loan loss provisions, and unreserved loan losses. The evidence in this chapter supports the oft-voiced concern that excessive flexibility in financial reporting undermines the ability of accounting signals to accurately capture the underlying financial health of banks. Obliqueness of the distressed bank's accounting signals makes such information less useful for investors and regulators, and thus has negative regulatory implications.

Chapter 4 focuses on the capital-related initiatives of Basel III and empirically examines three sets of assumptions that are implicit in Basel III capital regulation: (1) distress-relevance of bank regulatory capital, (2) poor loss-absorption properties of intangibles, such as deferred tax assets (DTA) and goodwill, and (3) the backstop role of risk-insensitive regulatory capital measures. Our key finding is on the information value of Basel risk weights (RW) in the context of predicting bank distress. Specifically, we show that the association between RWs and bank distress is statistically insignificant in the subset of large banks that predominately apply the Internal Rating Based (IRB) models, while it is positive and statistically significant for the small non-IRB banks. This finding is consistent with a concern that the IRB capital regulation may be subject to issues that hamper the association between banks' reported and real risks.

Chapter 5 studies the intended and unintended consequences of macroprudential policies (MaPs) by studying the behavior of bank credit, non-bank credit, total credit, and net sectoral credit flows, before and after the implementation of MaPs. Results confirm that MaPs reduce bank credit growth. In the 2 years after the implementation of MaPs, bank credit growth falls on average by 7.7 percentage points relative to the counterfactual of no measure. This effect is much stronger in EME than in AE. Beyond this, the analysis indicates that quantity-based measures have much stronger effects on credit growth than price-based measures, both in advanced and emerging market economies. Our main contribution to the literature is in our findings on substitution effects: the effect of MaPs on bank credit is always substantially above the effect on total credit to the private sector. Whereas bank credit growth falls on average by 7.7 percentage points relative to the counterfactual of no measure, non-bank credit increases after the implementation of MaPs so that total credit falls by 4.9 percentage points on average. Next to this general result we find remarkable differences between country groups and instruments. First, substitution effects are stronger in AEs. This is in line with expectations given their more developed financial systems, with a larger role for market-based finance. Second, substitution effects are much stronger in the case of quantity restrictions, which are more constraining than price-based measures. Moreover, we find strong and statistically significant effects on specific forms on non-banking financial intermediation, such as investment fund assets.

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