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Three essays on capital market effects of accounting information

Severin WIDMER

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La doyenne

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“Der Mensch verliert das Gleichgewicht seiner Stärke, die Kraft der Weisheit, wenn sein Geist für einen Gegenstand zu einseitig und zu gewaltsam hingelenkt ist.”

Johann Heinrich Pestalozzi, 1746-1827

Executive Summary

This dissertation comprises three distinct chapters. The first chapter examines market reactions towards changing the information location of own credit risk (OCR) gains and losses on financial liabilities designated at fair value (FVOL) from net income to other comprehensive income (OCI), as part of replacing IAS 39 by IFRS 9. Using event study methodology, I find that banks that have accumulated an OCR net gain (loss) since 2006 exhibit significantly lower (higher) abnormal returns. This result suggests that investors overvalued banks that accumulated an OCR net gain relative to banks that accumulated an OCR net loss prior to the events. Further analysis shows that the effect is solely present in low information environments, consistent with low information environments decreasing the effect of OCR gains and losses on firm valuations.

The second chapter examines the return relevance, value relevance, and risk relevance of OCR gains and losses on FVOL. Using a global sample of IFRS banks from 2006 to 2015, we find that recognized OCR gains and losses are negatively related to stock returns and stock prices, respectively, indicating that the market perceives OCR gains (losses) as a negative (positive) signal for the bank's economic performance. In addition, OCR gains and losses are risk relevant, as indicated by the positive correlation between the volatility in OCR gains and losses and the volatility in stock returns. Taken together, our findings suggest that recognized OCR gains and losses reflect changes in the entity-wide credit risk, i.e., the asset-side effect of credit risk changes dominates the liability-side effect.

The third chapter examines the capital market effects of standardized voluntary disclosure of industry-specific information in an ex-ante strong information environment, which is the European real estate sector. We compute three proxies measuring the degree of firm compliance with the best practice recommendations (BPR) issued by the European Public

Real Estate Association (EPRA). Our results show that EPRA NAV and EPRA NNNAV are both relatively and incrementally value relevant. Further, our results show that firms' increased (decreased) EPRA BPR disclosures are positively (negatively) associated with liquidity and analyst coverage and negatively (positively) associated with cost of capital. Lastly, we find that debt offering plans are positively associated with first-time adoption of EPRA BPR and subsequently the degree of compliance with EPRA BPR. Overall, our results indicate that investors and analysts deem complementary disclosures in accordance with EPRA BPR useful.

Keywords: Own credit risk (OCR), debt valuation adjustments (DVA), IFRS 9, IAS 39, fair value accounting, EPRA, best practice recommendations, standardized voluntary disclosure, banks and real estate firms, information asymmetry.

Résumé

Cette thèse consiste en trois chapitres distincts. Le premier chapitre examine les réactions du marché visant à modifier l'emplacement de l'information des profits et des pertes de risque de crédit propre (OCR) sur les passifs financiers désignés à la juste valeur (FVOL) du résultat net aux autres éléments du résultat étendu (OCI), dans le cadre du remplacement de l’IAS 39 par l’IFRS 9. À l'aide de la méthodologie de l'étude d’événements, je décèle que les banques qui ont accumulé un profit net (une perte nette) d’OCR depuis 2006 affichent des rendements anormaux nettement inférieurs (supérieurs). Ce résultat suggère que les investisseurs ont surévalué les banques ayant accumulé un profit net d'OCR relatif aux banques ayant accumulé une perte nette d'OCR avant les événements. Une analyse plus approfondie montre que l'effet est uniquement présent dans des environnements d'information inférieurs, consistent avec des environnements d'information inférieurs réduisant l'effet des profits et des pertes d'OCR sur les évaluations fermes.

Le deuxième chapitre examine la pertinence du rendement, de la valeur et du risque relative aux profits et aux pertes d'OCR sur FVOL. À l'aide d'un échantillon global de banques IFRS de 2006 à 2015, nous constatons que les profits et pertes d’OCR sont négativement associées aux rendements et aux prix du marché, ce qui indique que le marché perçoit les profits (pertes) d'OCR comme un signal négatif (positif) pour la performance économique de la banque. En outre, les profits et les pertes d’OCR sont pertinents pour le risque, comme la corrélation positive entre la volatilité des profits et des pertes de l'OCR et la volatilité des rendements des stocks l'indique. Pris ensemble, nos résultats suggèrent que les profits et les pertes d’OCR reflètent les changements dans le risque de crédit à l'échelle de l'entité, c'est-à-dire que l'effet sur l'actif des changements de risque de crédit domine l'effet du passif.

Le troisième chapitre examine les effets sur le marché des capitaux de la divulgation volontaire normalisée d'informations spécifiques à l'industrie dans un environnement d'information ex ante solide, qu’est le secteur immobilier européen. Nous calculons trois mesures approximatives capturant le degré de conformité des entreprises aux recommandations de bonnes pratiques (BPR) émises par l'European Public Real Estate Association (EPRA). Nos résultats montrent qu’EPRA NAV et EPRA NNNAV sont relativement et progressivement pertinents pour le prix du marché. En outre, nos résultats montrent que les divulgations EPRA BPR sont positivement (négativement) associées à la couverture de liquidité et aux analystes et négativement (positivement) associées au coût du capital. Enfin, nous constatons que les plans d'offre de créances sont positivement associés à la première adoption d'EPRA BPR et, par la suite, au degré de conformité avec EPRA BPR. Dans l'ensemble, nos résultats indiquent que les investisseurs et les analystes considèrent que les divulgations EPRA BPR sont pertinentes.

Mots clés : risque de crédit propre (OCR), ajustements d'évaluation de la dette (DVA), IFRS 9, IAS 39, comptabilité de la juste valeur, EPRA, recommandations de bonnes pratiques, divulgation volontaire normalisée, banques et sociétés immobilières, asymétrie de l'information.

Table of contents

List of tables

Chapter 3: Beyond IFRS: How Firms Benefit from Industry-Specific Reporting Guidance

Introduction

Accounting research is a very wide area of research that typically examines reportable information and its association with economic outcomes. Those economic outcomes can include but are not limited to capital market outcomes, stakeholder behavior, taxation, labor migration, regulatory changes, and the environment. To investigate the associations between reportable information and economic outcomes, academic accounting research focuses on three broad scientific methodologies, i.e., empirical research, experimental research, and analytical research.

This dissertation focuses on capital market outcomes of accounting information using empirical research methodologies. This stream of literature goes back to Ball and Brown (1968) and Beaver (1968) who adopt event-study methodology for accounting research purposes. Event studies infer whether certain events convey new information to market participants, which in turn leads to changes in level or variability of stock prices or trading volume over a certain period (Kothari, 2001). The two studies provide compelling evidence that earnings announcements convey new information to market participants. In addition, Ball and Brown (1968) is also one of the pioneering association studies in accounting. Association studies in market-based research test for significant correlation between reportable information and capital market outcomes. Ball and Brown (1968) find a positive correlation between accounting-based income numbers and stock returns.

Since then, empirical studies (e.g. association studies, causality studies, and path analysis studies) on the relation between accounting information and capital market outcomes have grown exponentially over time. These studies have helped us become more comfortable with the idea that there are certain interactions between accounting information and capital market outcomes. Nowadays, there is little disagreement that accounting information in general, and financial reports in particular, are a crucial primary source when investigating a company's performance. The increased reliance on accounting information and the increased complexity of today's economy have led to more complex and exhaustive financial reports; a trend that shows no sign of abating. However, it is still under research *whether* lengthier and more complex disclosures generally alleviate information asymmetries or *when* additional disclosures alleviate information asymmetries.

A more traditional view proposes that investors have unlimited processing capacity. This means that lengthy and complex disclosure is potentially beneficial because investors can efficiently process all information and, thus, can ignore irrelevant information. In this case, additional disclosure is never harmful. On the contrary, an alternative view proposes that lengthy and complex disclosure is costly to process and as such less likely to be informative as investors do not have unlimited processing power. Hence the ongoing proliferation of mandated disclosures that accompany financial reports make it difficult for investors to separate relevant information from boilerplate language, immaterial information, or repetitions to decipher a company's performance (Dyer, Lang, and Stice-Lawrence, 2016). In this view, disclosure overload can aggravate information asymmetries.

Some researchers argue (e.g. Cazier and Pfeiffer, 2015; Dyer, Lang, and Stice-Lawrence, 2016; and Guay, Samuels, and Taylor, 2016) that the increase in complexity and length of annual reports are primarily driven by complex fundamentals and increased mandated disclosures, two factors that are outside the control of the firm. Nevertheless, a company's management has at least some discretion over the complexity and length of financial statements. Management may decide to increase the complexity and length of financial statements for two opposing reasons: to obfuscate important information—such as poor performance (e.g. Li, 2008; Miller, 2010; Lawrence 2013; and Loughran and McDonald, 2014)—or to improve a complex information environment (e.g. Guay, Samuels, and Taylor, 2016).

My first two dissertation projects relate to the ongoing research on the complexity and length of disclosure by investigating own credit risk (OCR) gains and losses—an accounting topic that seems to be counter-intuitive and particularly difficult to understand even for knowledgeable financial statement users (Gaynor, McDaniel, and Yohn, 2011; Lachmann, Wöhrmann, and Wömpener, 2011; and Lachmann, Stefani, and Wöhrmann, 2015). OCR gains and losses arise because of value changes in financial liabilities designated at fair value due to changes in an entity's own credit risk. As such, an increase (decrease) in an entity's credit risk affects ceteris paribus the value of the financial liability in a negative (positive) and the value of comprehensive income in a positive (negative) manner.

The first chapter is motivated by the question whether information location matters. Therefore, I examine market reactions to IFRS 9 pronouncements for financial liabilities. Specifically, I investigate whether markets reacted to issuance of new information regarding the overhaul of IFRS for financial liabilities designated at fair value. Eventually, the IASB decided—to avoid causing undue disruption to current accounting practices—to keep the accounting treatment for financial liabilities essentially unchanged except for the presentation movement of OCR gains and losses from net income to other comprehensive income. In cross-sectional tests, I observe that banks that accumulated an OCR net gain (loss) showed significantly lower (higher) abnormal returns. This finding suggests that investors perceived banks that accumulated an OCR net gain as overpriced relative to banks that accumulated an OCR net loss. Further analysis shows that—splitting the sample into above- and below-median information environments—the association between the sign of the accumulated OCR net results remains strong for low information environments but vanishes for high information environments. The results are consistent with low information environments decreasing the effect of OCR gains and losses on firm valuations.

The results in the first chapter raise concerns whether investors not only struggle with the processing of OCR gains and losses but systematically misinterpret OCR gains (losses) as a signal that an entity's credit risk is improving (deteriorating). This concern has already been raised by prior experimental studies that show that knowledgeable financial statement users struggle with the interpretation of OCR gains and losses (Gaynor, McDaniel, and Yohn, 2011; Lachmann, Wöhrmann, and Wömpener, 2011; and Lachmann, Stefani, and Wöhrmann, 2015). In addition, critics of the recognition of OCR gains and losses claim that equity analysts and investors ignore OCR gains and losses, because they do not reflect economic performance (e.g. JP Morgan Chase, 2009). However, whether OCR gains and losses indeed do not convey useful information to investors remains an open question.

To tackle this question, Peter Fiechter (co-author) and I apply return-, value- and risk-relevance methodology in chapter two. Our empirical evidence suggests that—contrary to various claims that OCR should be ignored—OCR gains (losses) signal negative (positive) economic performance, i.e., are negatively related to stock returns and stock prices, respectively. The negative association between OCR gains and losses and stock returns and stock prices, respectively, also indicates that the asset-side effect of changes in credit risk dominates the liability-side effect. We also find that volatility in OCR gains and losses are positively related to stock volatility, i.e., are risk relevant. Taken together, the results suggest that OCR gains and losses yield—despite their complexity—useful information to investors. Additional tests corroborate our notion that investors do not systematically misinterpret OCR gains (losses) as a signal for positive (negative) future performance.

The third chapter relates to the ongoing research on the complexity and length of disclosures by investigating whether real-estate-specific voluntary disclosures beyond IFRS trigger capital market outcomes. Therefore, Jérôme Halberkann (co-author) and I focus on voluntary *standardized* disclosures in accordance with the European Public Real Estate

Association (EPRA) Best Practice Recommendations (BPR). EPRA BPR provide European real estate companies with guidance on (1) *what* information investors need—beyond IFRS financial statements—(2) *how* the information should be generated, and (3) *how* the information should be presented. The high level of detail in these recommendations is intended to decrease information processing costs in an arguably ex-ante rich information environment to further increase transparency and comparability among real estate firms. In this setting, we seek to examine the usefulness, the economic effects, and the determinants of EPRA BPR disclosures. More specifically, we investigate whether EPRA BPR disclosures convey useful information that is incorporated into stock prices; whether EPRA BPR disclosures can be associated with positive capital market effects such as higher liquidity, lower cost of capital, and higher analyst following that go beyond the effects of applying IFRS; and whether certain factors favor an EPRA BPR adoption. Using value-relevance methodology, we find that EPRA net asset value (NAV) and EPRA triple net asset value (NNNAV) are relatively and incrementally value relevant, whereas EPRA earnings per share (EPS) are neither relatively nor incrementally value relevant. In terms of capital market outcomes, firms committing to EPRA BPR are associated with increased liquidity, lower refinancing costs, and greater analyst coverage. In addition, we find that an upcoming debt offering provides an incentive for real estate firms to adopt EPRA BPR. Also, firms with weaker stock price performance, firms with upcoming debt offerings, and firms in countries with better legal quality tend to more strongly comply with EPRA BPR.

The results in the third chapter add to the literature by providing rationale for the widespread use of voluntary disclosures to alleviate information asymmetries. Understanding the economic effects of accounting disclosures is arguably of first-order importance, because it sheds light on the economic effects of disclosures in other areas such as product quality, consumer protection, conflicts of interests, environmental policy, health care etc. (Leuz and Wysocki, 2016).

Although there is already a vast amount of literature investigating the effect of voluntary disclosure in accounting, studies that allow for causal interpretations and studies that include path analysis remains rare due to their nature that these studies face a self-selection problem. Hence it remains an open question whether, for example, voluntary disclosure directly drives capital market outcomes; whether voluntary disclosure and capital market outcomes are a result of omitted variables; or whether voluntary disclosure affects omitted variables, which in turn trigger capital market outcomes. A recent path analysis study by Guay, Samuels, and Taylor (2016) suggest that voluntary disclosure in form of management forecasts may help mitigate the negative effects of complex financial statements. Still, how voluntary disclosures, capital market outcomes, and analyst coverage are interrelated remains an open question.

References

Ball, R. and Brown, P. 1968. An empirical evaluation of accounting income numbers. *Journal of Accounting Research* (6): 159–178.

Beaver, W.H. 1968. The Information content of annual earnings announcements. *Journal of Accounting Research* (6): 67–92.

Cazier, R.A. and Pfeiffer, R.J. 2015. Why are 10-K fillings so long? *Accounting Horizon* (30): 1–21.

Dyer, T., Lang, M. H., and Stice-Lawrence, L. 2016. Do managers really guide through the fog? On the challenges in assessing the causes of voluntary disclosure. *Journal of Accounting and Economics* (62): 270–276.

Gaynor, L.M., McDaniel, L., and Yohn, T.L. 2011. Fair value accounting for liabilities: The role of disclosure in unraveling the counterintuitive income statement effect from credit risk changes. *Accounting, Organizations and Society* (36): 125–134.

Guay, W., Samuels, D., and Taylor, D. 2016. Guiding through the fog: Financial statement complexity and voluntary disclosure. *Journal of Accounting and Economics* (62): 234–269.

JP Morgan Chase. 2009. Comment letter (CL99) on the discussion paper on credit risk in liability measurement. Retrieved from http://www.ifrs.org/Current-Projects/IASB-Projects/Credit-Risk-in-Liability-Measurement/DP-Jun-09/Comment-Letters/Pages/Comment-letters.aspx.

Kothari, S.P. 2001. Capital market research in accounting. *Journal of Accounting and Economics* (31): 105–231.

Lachmann, M., Stefani, U., and Wöhrmann, A. 2015. Fair value accounting for liabilities: Presentation format of credit risk changes and individual information processing. *Accounting, Organizations and Society* (41): 21–38.

Lachmann, M., Wöhrmann, A., and Wömpener, A. 2011. Acquisition and integration of fair value information on liabilities into investors' judgement. *Review of Accounting and Finance* (10): 385–410.

Lawrence, A. 2013. Individual investors and financial disclosure. *Journal of Accounting and Economics* (56): 130–147

Leuz, C. and Wysocki, P. D. 2016. The economics of disclosure and financial reporting regulation: Evidence and suggestions for future research. *Journal of Accounting Research* (54): 525–622.

Li, F. 2008. Annual report readability, current earnings, and earnings persistence. *Journal of Accounting and Economics* (45): 221–247.

Loughran, T. and McDonald, B. 2014. Measuring readability in financial disclosure. *Journal of Finance* (69): 1643–1671.

Miller, B.P. 2010. The effects of reporting complexity on small and large investor trading. *The Accounting Review* (85): 2107–2143.

Chapter 1: Market Reactions towards IFRS 9 Pronouncements

1.1. Introduction

The International Accounting Standards Board (IASB) published the final version of International Financial Reporting Standard 9 (IFRS 9) in July 2014 as a reaction to the increasing criticism of the timeliness of recognition of expected credit losses, the complexity of multiple impairment models, and own credit risk (OCR) recognition for financial liabilities designated at fair value (FVOL) (IASB, 2014c). Related to OCR, the practice of recognizing changes in OCR has been criticized because an entity reports a gain (loss) from a decline (increase) in credit quality, through a decrease (increase) in FVOL (IASB, 2009). To avoid causing undue disruption to accounting practices, the IASB decided to keep the accounting treatment of FVOL essentially unchanged except for the presentation location of OCR gains and losses. Whereas prior International Accounting Standard 39 (IAS 39) stipulates recognition of OCR gains and losses through profit or loss, IFRS 9 generally stipulates recognition through other comprehensive income (OCI). The IASB believes that the new presentation location helps investors process OCR gains and losses without losing useful information about the implications of the changes in credit risk (IASB, 2010).

In this paper, I examine market reactions to IFRS 9 pronouncements regarding the treatment of FVOL. Specifically, I investigate whether markets reacted to the events when the IASB released new information (e.g. discussion papers, exposure drafts, final standards) regarding the standard overhaul process affecting the accounting treatment of FVOL. In a perfectly efficient market, where all information is processed by investors and reflected in stock prices, I should be unable to detect any significant market reaction because the change in presentation location is unlikely to change the underlying economics of an entity.[1] However, prior experimental studies find that investors' view about the association between OCR gains and losses and firm performance can be biased (Gaynor, McDaniel, and Yohn, 2011; Lachmann, Wöhrmann, and Wömpener, 2011; and Lachmann, Stefani, and Wöhrmann, 2015). In addition, studies show that the quality of processing OCR gains and losses may depend on the information location and that information presented in a salient, easily processable form can better be absorbed by investors (Lachmann, Stefani, and Wöhrmann, 2015). The increased public information and the heated debate during the standard overhaul process on the accounting treatment of FVOL and the recognition of OCR gains and losses may have influenced investors' assessment of how to incorporate OCR gains and losses in firm valuations. Such adjustments can induce market reactions. Focusing on banks, I conjecture that market reactions are likely to depend on whether banks accumulated an OCR net gain or a net loss since the fair value option for financial liabilities became first effective in 2006. Investors may have overvalued banks that accumulated an OCR net gain relative to banks that accumulated an OCR net loss because of the widespread misconception that OCR gains (losses) signal a credit risk improvement (deterioration). I further conjecture that such misconceptions are likely to be more pronounced in weaker information environments.[2] Specifically, country-specific variation in information environments (e.g. stock market development) and bank-specific variation in information environments (e.g. analysts following) may affect the market reactions.

To investigate whether the new regulations for FVOL under IFRS 9 induced market reactions, I structure my research design as follows: First, I examine overall stock market reactions towards the new regulations. I market-adjust the raw returns around the four major

[1] Bank-specific regulatory requirements such as Basel III stipulate exclusion of OCR gains and losses from the calculation of Common Equity Tier 1. This exclusion is not affected by IFRS 9.

[2] Maffett (2012), for example, shows that there is considerable variation in information environments across countries.

steps towards the final standards using a one-factor market model to mitigate the effect of potential confounding events. Because I use stock return data with common event dates across banks—raising concerns about cross-sectional correlation—I build an equally-weighted portfolio of 144 IFRS-banks and run the tests on a portfolio level (Sefcik and Thompson, 1986). I compute abnormal returns relative to both the STOXX Global 1800 ex North America index and the STOXX Global 3000 Bank index to mitigate concerns that the results are driven by the choice of a certain market index.

Second, I assess whether abnormal returns are associated with the sign of the accumulated OCR net gains or losses using cross-sectional variation in accumulated OCR gains and losses. I define a dichotomous variable that differentiates between two subgroups of banks: (1) IFRS-banks with FVOL that have accumulated an OCR net gain since 2006 and (2) IFRS-banks with FVOL that have accumulated an OCR net loss since 2006. I control for bank characteristics, stock characteristics, environment characteristics, country-fixed effects, and event-fixed effects to control for (un-)observable differences that may influence the relation between accumulated OCR net gains and losses and abnormal returns. I further investigate whether the association between accumulated OCR net gains and losses and abnormal returns are linked to the information environment. I perform two additional tests where I exploit country-specific and bank-specific variation in information environments. Following Beck and Levine (2002) and Fiechter and Novotny-Farkas (2017), I classify countries into market-based and bank-based economies and repeat the previous regression for the two subsamples. In addition, I classify banks into high-analyst (low-analyst) following based on whether the average number of analysts following is above (below) the sample-median and, again, repeat the previous regressions for the two subsamples.

Third, because my findings are premised to the notion that daily stock returns are generally unrelated to OCR net gains and losses, I re-examine the association between OCR net gains and losses and abnormal returns during non-event days. I randomly select four non-overlapping three-day event windows between 2008 and 2010 and re-estimate the main regressions on non-event days. I repeat this procedure one thousand times and test whether the means of the non-event coefficients are significantly different from the coefficients in the event regressions.

Empirical results show that the portfolio overall market reaction tends to be slightly negative. However, the findings turn out significantly negative only when using the STOXX Global 3000 Bank index and an event window t=(0) or t=(-1,0,+1). Using the STOXX Global 1800 ex North America index or a wider event window t=(-4,-3,-2,-1,0,+1) does not exhibit any significant portfolio overall market reactions. This result is in line with investors viewing banks that accumulated an OCR net gain as overvalued at the time of the events, as the mean of OCR net gains and losses in the sample is positive.

In the cross-sectional analysis, I observe strong results that banks that accumulated an OCR net gain (loss) show significantly lower (higher) abnormal returns. This finding underpins the notion that investors viewed banks that accumulated an OCR net gain as overvalued at the time of the events relative to banks that accumulated an OCR net loss. When I split the sample into above-median and below-median information environments, I observe that the association between the sign of the accumulated OCR net gains or losses and the abnormal returns is strong for low information environments only. The results are consistent with low information environments decreasing the effect of OCR gains and losses on firm valuations.

Simulation results corroborate that the effect is unique to the event days and, therefore, is likely to be driven by IFRS 9 pronouncements rather than misspecification such as omitted variable bias.

To further bolster my results, I examine whether not only the sign but also the magnitude of the accumulated OCR net gains and losses is associated with the abnormal returns by exchanging the dichotomous OCR variable by a continuous measure. I find a weaker negative association between the magnitude of the OCR net gains and losses and the abnormal returns. Still, four out of eight model specifications show significantly negative OCR coefficients and all model specifications exhibit the expected negative sign. To further mitigate concerns that my results are driven by country-specific effects that are unrelated to IFRS 9 pronouncements, I perform the main regressions on a subsample of four countries within Europe, which provide the most OCR-gains-and-losses data for my analyses.[3] The small sample regressions show results that remain fully in line with previous results, suggesting that it is unlikely that the results are driven by effects that are specific to countries where OCR data is sparse.

Collectively, I find robust evidence on a negative relation between the sign of the accumulated OCR net gains or losses and abnormal returns towards new regulations for FVOL under IFRS 9. However, the findings include an important caveat—they rely heavily on a correct event identification where the time of relevant new information issuance lies within the event windows and major confounding events are excluded from the estimation.

Understanding the effect of the change in presentation location of OCR gains and losses on stock prices is important for several reasons: First, although banks that apply the fair value option designate, on average, only between 9.69% (2006) and 6.75% (2012) of their financial liabilities at fair value, OCR gains and losses can be substantial. From 2006 to 2012, OCR gains and losses ranged from gains of USD 6.6 billion to losses of USD 7.5 billion. Hence misinterpreting OCR gains and losses may materially distort investors' assessment of an entity’s value. Second, credit risk is arguably banks single-most important risk factor. Their exposure to credit risk due to their underlying business model translates directly into bank’s

[3] 66.1% of the data on OCR gains and losses comes from banks that are located either in Germany, Italy, Switzerland, or the UK.

OCR. Hence understanding the implication of changes in credit risk on assets, liabilities, and comprehensive income should be a major concern.

The paper proceeds as follows: Section 1.2 provides background information, a literature review and the hypotheses development. Section 1.3 outlines the sample selection and descriptive statistics. Section 1.4 describes the research design. Section 1.5 presents the empirical results. Section 1.6 discusses additional analyses. Section 1.7 concludes.

1.2. Background

1.2.1. International Financial Reporting Standards for Financial Liabilities

Currently, IFRS require that financial liabilities are initially recognized at fair value plus transaction costs and subsequently recognized at amortized cost using the effective interest method. The effective interest method is based around the effective interest rate, the rate that discounts all contractual fees and points paid or received between parties through the expected life to the net carrying amount. Thus, the effective interest rate incorporates debt's market rate and, in turn, the borrower's credit risk, collateral, and guarantees. Interest expenses are calculated using the effective interest and are allocated over the periods until maturity.

As an alternative to amortized cost measurement, firms may irrevocably designate at initial recognition to measure financial liabilities at fair value through profit or loss. Those FVOL are initially recognized at fair value without incorporating transaction costs. Subsequently, FVOL are measured at fair value with gains and losses recognized in profit or loss (IASB, 2013).

Generally, making use of the fair value option for financial liabilities is not a widespread occurrence amongst banks that prepare their financial statements in accordance with IFRS. In my sample, only 8.9% of total debt is, on average, classified as FVOL. Beside the fair value option, IAS 39 further requires fair value accounting for derivatives unless they are linked to and must be settled by delivery of an unquoted equity instrument whose fair value cannot be reliably measured.

Many financial statement preparers, users, and auditors have criticized IAS 39 for being too complex. They urged the IASB and the FASB to develop new standards on financial instruments that are principle-based and less complex (IASB, 2008). Meanwhile, the controversial debate over whether measurement of financial liabilities should reflect changes in a company's OCR through profit or loss flared up again. Some argue that incorporating credit risks into profit or loss is consistent with the initial measurement of financial liabilities—including the effects of the borrower's credit risk—and that it better represents the wealth transfer between equityholders and debtholders. As debtholders have a fixed claim, equityholders receive all the upside gains but share the downside losses with debtholder. An unexpected deterioration of credit quality increases the likelihood that debtholders lose (part of) their investment. The result is a wealth transfer from debtholders to equityholders. Others argue that it is counterintuitive if an entity reports a gain from a decline in credit quality and that financial liabilities should be measured at amortized cost because liabilities are seldom transferred, i.e., firms seldom realize value changes in FVOL (IASB, 2009).

In March 2008, the IASB published a discussion paper *Reducing Complexity in Reporting Financial Instruments* that marked the beginning of the standard overhaul process for financial instruments. First, the IASB considered examining the issue of credit risk in liability measurement as an independent project. In October 2009, the IASB decided to stop working on credit risk as a free-standing work stream and to integrate the topic in the project on the classification and measurement of financial instruments. In February 2014, the IASB finalized deliberations on the limited amendments to classification and measurement of financial instruments.

IFRS 9—which supersedes IAS 39—retains the requirement to measure financial liabilities initially at fair value and subsequently at amortized cost using the effective interest method. The option to irrevocably designate financial liabilities at fair value remains eligible if the information leads to more relevant information. Generally, IFRS 9 mandates that changes in the fair value of financial liabilities attributable to changes in OCR need to be presented in OCI. Only in cases where OCR gains and losses through OCI creates or enlarges an accounting mismatch, should a firm continue to show OCR gains and losses in profit or loss. An accounting mismatch arises when the effects of changes in a liability's credit risk are expected to be offset by changes in the fair value of other financial instruments. An assessment of an accounting mismatch is required at initial recognition and is not reassessed (IASB, 2014b). IFRS 7 requires qualitative disclosure in the financial statements notes of the methodology of assessing whether there is an accounting mismatch (IASB, 2014a). The amount of change in the fair value of a financial liability attributable to changes in OCR should be determined either as the amount not attributable to market risk or using an alternative method that directly estimates the amount attributable to credit risk. Changes in market risk can be measured by means of a benchmark interest rate, the price of a firm's financial instruments, a commodity price, a foreign exchange rate, or an index of prices or rates. Changes in fair value of financial liabilities attributable to market risk need to be presented in profit or loss (IASB, 2014b).

Initially, the IASB set January 1, 2013 as the mandatory effective date for application of IFRS 9. However, the effective date was first postponed to January 1, 2015. With the release of the final standard, the effective date was further postponed to January 1, 2018.

1.2.2. Literature Review and Hypotheses Development

One research stream relating to OCR gains and losses examines how changes in credit risk affect the value of equity and debt. Strong (1990) presents a disaggregated approach to measuring market value of debt. He separates debt-holding gains and losses into changes in credit risk and unanticipated inflation. The findings show that the effects of changes in credit risk and unanticipated inflation on bond value and stock value are both material and statistically significant. The disentangling of the two effects shows that increases in credit risk are negatively correlated with both equity and debt values and that there is a wealth transfer between bondholders and stockholders. Holthausen and Leftwich (1986) and Goh and Ederington (1993) investigate the effect of credit rating changes on stock returns. They find that unanticipated downgrades, i.e., credit risk increases, are associated with negative abnormal returns around the events. Barth, Hodder, and Stubben (2008) test whether equity value changes associated with credit risk changes are attenuated by debt value changes. They find that the relation between credit risk changes and equity returns is significantly less negative for firms with more debt. Controlling for asset value changes, credit risk increases (decreases) are associated with equity value increases (decreases) through decreases (increases) in debt value. However, for a substantial majority of downgrade firms they find that recognized asset write-downs exceed unrecognized gains from debt value decreases. Lipe (2002) demonstrates that financial ratios can produce unwarranted positive signals when measuring financial liabilities at fair value through profit or loss for firms that experience severe credit deteriorations. Lipe (2002) acknowledges that his results are primarily driven by poor and incomplete accounting choices for asset valuation and that if the accounting for all items was perfect, then any positive signal from writing down financial liabilities would likely be outweighed by other negative signals. Lipe (2002) concludes that if standard setters ultimately determine that fair value is the best measure for the statement of financial positions, some of the misleading signals could be avoided by placing gains and losses attributable to changes in credit quality in OCI.

Another more recent research stream—relating to the interpretation of OCR gains and losses—shows that financial statement users have difficulties identifying and processing OCR gains and losses. Gaynor, McDaniel, and Yohn (2011) conduct an experimental study with CPAs where they find that over 70% of participants misinterpret a gain (loss) due to changes in firm's OCR as credit risk improving (deteriorating). Even if CPAs are given disclosure that explicitly specifies the relation between a credit risk change and net income—neither mandated by IAS 39 nor IFRS 9—misinterpretation of the OCR gains and losses continue to be around 50%. They conclude that additional disclosure can reduce misinterpretation only partially and that standard setter should, therefore, consider relegating credit risk gains and losses from net income to OCI. Lachmann, Wöhrmann, and Wömpener (2011) confirm the previous result that OCR gains and losses are counterintuitive for knowledgeable financial statement users. In addition, they find that changes in credit risk are more likely to remain unnoticed if they are not recognized but only disclosed. Lachmann, Stefani, and Wöhrmann (2015) conduct an experiment with auditors and find that participants are more likely to identify the information on changes in credit risk if the information is included in OCI rather than net income. They argue that items presented in net income usually outnumber those in OCI and, as a result, it is more difficult for participants to extract the relevant information from net income than from OCI. However, the risk of misinterpreting the directional relation between credit risk and the comprehensive income is unaffected by the information location. The study is consistent with the notion that information presented in a salient and easily processable form is absorbed more easily by auditors (Hirshleifer and Teoh, 2003).

I argue that—based on the aforementioned studies—market inefficiencies are likely to exist in the form of imperfect OCR information processing. More specifically, difficulties in identifying relevant OCR information and assessing the ramifications of OCR gains and losses on entity's performance may have biased investors' assessment of firm valuation. For firms that accumulated an OCR net gain since 2006, firm value was likely overpriced relative to firms that accumulated an OCR net loss because of two reasons: First, if investors do not find OCR gains or losses in an income statement, they are likely to use OCR gains and losses fully for firm valuation through the inclusion of trading income and trading expenses. Second, if investors are able to identify OCR gains and losses but misinterpret the directional relation on firm's performance, they are likely to overprice firms that accumulated an OCR net gain. Correcting those misinterpretations should induce negative market reactions for firms that accumulated an OCR net gain relative to firms that accumulated an OCR net loss.

Investors' ability to process information may depend on the sophistication of the information environment. Maffett (2012) shows that investor sophistication varies substantially across countries. To investigate differences in market sophistication, Beck and Levine (2002) and Fiechter and Novotny-Farkas (2017) classify countries into market-based and bank-based countries. The institutional features of market-based economies exhibit higher stock market development, higher disclosure standards, and stronger information environment. Hence market-based countries are more likely to process OCR gains and losses correctly (Fiechter and Novotny-Farkas, 2017). In addition, firm-specific information environment may also influence the processing of OCR gains and losses and, therefore, the market reactions.

1.2.3. Event Identification

Although the shift of OCR gains and losses from profit or loss to OCI was a continuous process with considerable discussions, I identify four major steps towards the finalization of the new regulations for FVOL under IFRS 9. Events are identified by, first, going through all project stages towards IFRS 9, starting with the discussion paper *Reducing Complexity in Reporting Financial Instruments* to the finalization of IFRS 9 *Classification and Measurement*. Second, I screen the IASB and FASB meeting summaries to identify the major steps towards finalizing IFRS 9. FASB meeting summaries are considered because FASB's decisions are likely to have an impact on the IASB's discussions and vice versa. Third, I examine available listings of documents publicly released by the IASB, the European Financial Reporting Advisory Group (EFRAG), the Standard Advice Review Group (SARG), the Accounting Regulatory Committee (ARC), the European Parliament, the Council of the European Union, and the European Commission (EC). Fourth, I search the Factiva database by Dow Jones & Company Inc. and the Thomson Reuters Eikon database for potential confounding events.[4]

Eventually, I consider *major steps* to be events when the IASB issues new publications to the public, such as discussion papers, exposure drafts, and final standards. Those publications are stronger signals how the final IFRS 9 might look like than meeting summaries. Also, IASB publications seem to be timelier than press releases as press releases often provide delayed summaries of the IASB publications. This way, I only consider events that provided new information to the market and I do not consider events that simply process information for another audience. In addition, I do not identify any pattern of good or bad news that systematically affects the stock returns during my events. Further, I focus on publications that are not only related to IFRS 9 but more specifically to FVOL because IFRS 9 does not only stipulate standards for the measurement of FVOL but also for the measurement of other financial instruments, for the impairment of financial instruments, and for hedge accounting. I focus on a small number of events that are most likely to have a significant influence on stock prices. This approach is more likely to isolate the effect of the change in information location

[4] Factiva had initially been founded under the name Dow Jones Reuters Business Interactive but changed its name six months later in May 2009 to Factiva.

of OCR gains and losses from other concurrent events. Further, focusing on a small number of events should produce less noise and exhibit more accurate regression results. However, if stock returns were influenced by concurrent events, results can be biased. To mitigate this issue, I drop abnormal returns from the sample if event dates coincided with earning releases and shareholder meetings.

On (1) March 19, 2008 the IASB issued the discussion paper *Reducing Complexity in Reporting Financial Instruments* to initiate the process of developing new regulations for financial instruments. Many preparers had urged the IASB and FASB to amend IAS 39 to become more principle-based and less complex. The IASB proposed the following approach to mitigate those concerns:

> *Unrealized gains and losses on interest-bearing financial liabilities attributable to changes in the entity's own credit risk must be recognized in other comprehensive income. An entity could also choose to report a specific percentage of gains or losses on these financial instruments in earnings and the remainder in other comprehensive income* (IASB, 2008, 2.49(c)).

However, the discussion paper did not ask readers to express their opinion on the proposed approach.

On (2) June 18, 2009 the IASB issued the discussion paper *Credit Risk in Liability Measurement* together with the corresponding staff paper.[5] Both papers invited readers to comment on predefined questions by September 1, 2009 without disclosing any new information on the standard overhaul process. The discussion paper sought comments on three possible approaches on liability measurement set out in the staff paper. Those

[5] The accompanying staff paper provides additional information, illustrations, and a variety of arguments to readers to better be able to respond to the questions asked.

approaches identified possible ways to measure liabilities while always excluding OCR gains and losses from profit or loss.[6,7]

On (3) May 11, 2010 the IASB issued the exposure draft *Fair Value Option for Financial Liabilities*. On the basis of the feedback received from its Financial Instruments Working Group and from 123 comment letters, the IASB decided that none of the three approaches suggested in the second discussion paper would be any less complex or would result in more useful information than the requirements in IAS 39. The IASB proposed that OCR gains and losses on FVOL should be presented in OCI unless such treatment would create a mismatch in profit and loss. The IASB received 138 comment letters as a result of the exposure draft *Fair Value Option for Financial Liabilities*. Those were carefully studied and incorporated into the development of IFRS 9. However, measurement of OCR gains and losses remained unchanged.

On (4) September 28, 2010 the IASB published the standards relating to the classification and measurement of financial liabilities and financial assets. Those standards amended the measurement of FVOL such that OCR gains and losses should no longer be presented in net income but in OCI, unless such treatment would create or enlarge an accounting mismatch in profit and loss. The remaining amount of the change in the FVOL should remain in profit or loss. Table 1.1 summarizes the four event windows.

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[6] Between the issuance of the discussion paper *Credit Risk in Liability Measurement* and the comment letters hand-in deadline, on July 14, 2009, the IASB issued the exposure draft *Financial Instruments: Classification and Measurement*. The publication of the exposure draft is not included as an additional event because it does not provide any information on financial liabilities.

[7] On October 21, 2009, the IASB stopped working on credit risk as a free-standing work stream and decided to incorporate the topic in the conceptual framework measurement project. Further, the board decided not to change the role of credit/performance risk in the definition of fair value as a result of the responses to the discussion paper.

1.3. Sample and Summary Statistics

1.3.1. Sample Selection Process

I examine investors' perception of the major steps towards new regulations for FVOL under IFRS 9 by focusing on banks' abnormal returns during four events. My tests require data on daily stock returns, firm characteristics, stock characteristics, and information environment characteristics. I draw my sample of IFRS-banks from Bankscope; financial data from Thomson Reuters Eikon; analyst data from I/B/E/S; data on U.S. cross listings from Bankscope; data on the regulatory quality of each country from the index by Kaufmann, Kraay, and Mastruzzi (2009); and data on country-specific information quality from Fiechter and Novotny-Farkas (2017). Data on FVOL, including OCR gains and losses in accordance with IAS 39, is hand-collected from annual reports. The overall sample period spans from 2008 to 2010 except for daily stock returns that cover a period from 2007 to 2010—to estimate abnormal returns—and cumulative OCR gains and losses that cover a period from 2006 to 2010—to calculate the accumulated OCR gains and losses since the introduction of the fair value option in 2006. I focus on the banking sector because banks' balance sheets consist primarily of financial instruments.

I start with an initial IFRS-bank sample of 5,109 banks. First, I exclude inactive banks (-1,174 banks) from the sample because they are not impacted by the new accounting standards for financial instruments. I focus on commercial banks and saving banks (-2,021 banks); ultimate owners (-1,566 banks) to examine data on the holding companies only; and banks that are located outside of North America and South America (-13 banks) to reduce continent-specific variation.[8] The sample before any further data collection consists of 335 IFRS-banks.[9] I drop banks from the sample if they have not been quoted on any stock exchange (-126 banks); if share prices do not move on more than 20% of trading days (-39 banks); and if

[8] None of the 13 IFRS-banks in America used the fair value option for financial liabilities.
[9] I loosely use the word *banks* as an acronym for bank holding companies.

banks show no movements in share prices during any of the four event windows (-8 banks). The sample for the event study consists of 162 IFRS-banks and 648 observations. Observations with missing data on any of the explanatory variable were dropped (-108 observations) and if event dates coincide with earnings releases or annual meetings (-34 observations). The sample available for empirical tests comprises 506 observations from 151 banks and 35 countries. Of those observations, 196 observations from 63 banks can be observed in 12 countries where OCR recognizers are present. The sample of OCR recognizers comprises 109 observations from 35 banks in 12 different countries. Table 1.2 outlines the sample selection process.

1.3.2. Descriptive Statistics

Table 1.3 presents descriptive statistics for the variables used in this paper. Table 1.3, Panel A reveals that the mean of the abnormal returns using the STOXX Global 1800 ex North America index (*ar_exna_3)* and the STOXX Global 3000 Banks index (*ar_banks_3)* for the full sample are close to zero (-0.003 and -0.007, respectively) and close to the median (-0.004 and -0.005, respectively). I find that 35.2% of the firm-events use FVOL, 21.5% of the firm-events disclose OCR gains and losses, and 12.1% of firm-events have accumulated an OCR net gain since 2006. FVOL users tend to be larger banks (*size*), with higher leverage ratios (*lev*), lower tier-1 ratios (*TIER 1*), lower proportion of closely held shares (*chs*), more cross-listed stock (*CL*), and are more likely to found in countries with higher regulatory quality (*regulatory quality*).

Table 1.3, Panel B reports firms (*Unique firms*) and firm-events (*Firm-events*) by country. Firm-events are separated into three subsamples include (1) observations with zero FVOL (*Non-FVOL users*), (2) observations with positive amounts of FVOL (*FVOL users*), and (3) observations with disclosure of OCR gains and losses (*OCR recognizers*), which is a subsample of *FVOL users*. Further, I tabulate mean abnormal returns calculated using both the STOXX Global 1800 ex North America index (*ar_exna_3*) and the STOXX Global 3000 Banks index (*ar_banks_3*). I also provide continuous data on the financial market structure (*Information environment*) as measured in Fiechter and Novotny-Farkas (2017). Countries with at least one bank that discloses OCR gains and losses are classified as market-based (bank-based) if *Information environment* is above (below) median. Untabulated statistics reveal that abnormal returns are similar for market-based and bank-based economies. Lastly, I provide data on the regulatory quality (*Regulatory quality*) as measured by Kaufmann, Kraay, and Mastruzzi (2009) for the year 2008. Table 1.3, Panel B highlights that disclosure of OCR gains and losses are most concentrated amongst Italy (24.8%), the United Kingdom (19.3%), Germany (11.0%), and Switzerland (11.0%).

Table 1.3, Panel C provides descriptive Pearson's correlation below the diagonal and Spearman's rank correlations above the diagonal for the variables used in the cross-sectional analysis. Those correlations provide first descriptive evidence that abnormal returns (*ar_exna_3* and *ar_banks_3*, respectively) tend to be negatively correlated with the dichotomous variable equal to one if a bank has accumulated on OCR net gain and zero otherwise (*POS CUM* OCR) and the magnitude of accumulated OCR gains and losses (*cum ocr*), respectively.

1.4. Research Design

1.4.1. Overall Market Reactions

Following the extensive literature on event-studies, I market-adjust raw event returns using a simple one-factor market model to mitigate the effect of potential confounding events (e.g. MacKinlay, 1997).[10] The market model parameters are estimated over the period from 11 to 250 days before the first event on March 19, 2008. Because I use a sample comprising only of banks that are located outside of America, choosing an appropriate market index is not obvious. I market-adjust raw returns for the three-day event-window t=(-1,0,+1) using the STOXX Global 1800 ex North America index and the STOXX Global 3000 Banks index.[11] The STOXX Global 1800 ex North America includes firms from all industry sectors that are located outside of North America. The STOXX Global 3000 Banks index includes banks from around the world. I do not use a broader index because that would raise concerns about adding unrelated variation, which can bias my results. I also do not use a narrower index like the STOXX Global 1800 ex North America Banks index because the index is very similar to my sample composition.

I start to examine market reactions towards the development of new regulations for FVOL under IFRS 9 by examining abnormal returns on days that lie within the event windows. For each firm-day within the event windows, I compute abnormal returns relative to the STOXX Global 1800 ex North America index and the STOXX Global 3000 Bank index. I compute cumulative abnormal returns for three different time windows, i.e., 1-day window t=(0), 3-day window t=(-1,0,+1), and 6-day window t=(-4,-3,-2,-1,0,+1). I present cumulative abnormal returns for each of the four events (CAR) and aggregated over all events (CCAR). Because I use stock return data with common event dates across banks, I am likely to find cross-sectional correlation. To remedy this concern, I base my test statistics on equally-weighted portfolio returns. Portfolio returns are not affected by potential cross-sectional correlation (Sefcik and Thompson, 1986) and are assumed to be uncorrelated across different

[10] Employing a multi-factor model for short-term event studies has been shown to have limited explanatory power over a one-factor model (e.g. MacKinlay,1997). Hence I focus on using a one-factor model.
[11] For descriptive purposes I also present abnormal returns for the one-day t=(0) and the six-day t=(-4,-3,-2,-1,0,+1) event windows.

time windows. However, a portfolio approach is not applicable in cross-sectional analyses, because all firm-specific abnormal return variation would be lost.

1.4.2. Cross-Sectional Analysis

My main inferences are based on the cross-sectional variation in market reaction to the new regulations for FVOL under IFRS 9. In particular, I assess whether abnormal returns are associated with the sign of the accumulated OCR net gain or loss over time. To measure this effect, I introduce a dichotomous variable *POS CUM OCR* equal to one if the bank accumulated an OCR net gain since 2006, and zero if the bank accumulated an OCR net loss. To obtain my inferences, I estimate the following model:

$$ar_{i,e} = \beta_0 + \beta_1\, POS\ CUM\ OCR_{i,e} + \sum_{j=1}^{J} \gamma_j\, Controls_{j,i,e} + \sum_{f=1}^{F} \delta_f\, Fixed\ Effects_{f,i,e} + \varepsilon_{i,e} \qquad (1)$$

where *ar* is the cumulative abnormal return for bank *i* during event *e* relative to the STOXX Global 1800 ex North America index and the STOXX Global 3000 Banks index, respectively. *Controls* is a vector of control variables including *size*, *roa*, *p/b*, *TIER 1*, *std*, *lev*, *chs*, *CL*, *spread*, and *regulatory quality*. *Fixed Effects* is a vector of *country-fixed effects* and *event-fixed effects*.

size is the natural logarithm of total assets. *roa* is the return on asset calculated as income after tax divided by total assets. *p/b* is the price-to-book ratio calculated as market capitalization divided by total book value of equity. *lev* is the leverage ratio calculated as total liabilities divided by total book value of equity. *TIER 1* is a dichotomous variable equal to one if the core equity capital divided by total risk-weighted assets is above the sample median and zero otherwise. *chs* is the percentage of closely held shares calculated as one minus free floating shares divided by total shares outstanding. *CL* is a dichotomous variable equal to one if the company has stock that is cross listed on a U.S stock exchange and zero otherwise. *std* is the standard deviation of a bank's stock returns during a calendar year. *spread* is the yearly median bid-ask spread calculated as the difference between the bid and ask price divided by the mid-point measured at the end of each trading day. *regulatory quality* is the regulatory quality in accordance with the index by Kaufmann, Kraay, and Mastruzzi (2009) for the year 2008. Generally, dichotomous variables are labeled in capital letters. T-statistics are calculated using White (1980) heteroscedasticity-consistent standard errors controlling for event-fixed effects and country-fixed effects (Petersen, 2009; Gow, Ormazabal, and Taylor, 2010; and Gormley and Matsa, 2014).

To further investigate whether variation in market reactions are associated with the information environment, I perform two additional tests. First, following Beck and Levine (2002) and Fiechter and Novotny-Farkas (2017), I calculated for each country the first principal component of two variables that measure the comparative activity and size of stock markets relative to the number of banks in this country. I focus on countries with at least one bank disclosing OCR gains and losses in the annual statement. Countries with above (below) median are defined market-based (bank-based) economies. Second, I exploit variation in the information environment on a firm-level based on the number of analysts following. I classify banks as high Analysts (low Analysts) if the number of analysts following is above (below) median. The median is calculated using only banks that accumulated OCR gains and losses, i.e. OCR recognizers. Then I re-estimate the main model separately for market-based and bank-based countries and for high-analyst and low-analyst banks.

1.4.3. Monte Carlo Simulation

My cross-sectional findings are premised to the notion that daily stock returns are generally unrelated to OCR gains and losses on non-event days. In other words, I assume that absent the development of new regulations for financial liabilities, *POS CUM OCR* is zero. However, one important alternative is that misspecification or omitted variables, correlated with the new regulations, drives the relation between the two (e.g. Cremers and Nair, 2005; Core, Guay, and Rusticus, 2006; Bebchuk, Cohen, and Ferrell, 2009; Armstrong, Barth, Jagolinzer, and Riedl, 2010; Gompers, Ishii, and Metrick, 2010; and Larcker, Ormazabal, and Taylor, 2011). If this is the case, I expect *POS CUM OCR* to be related with abnormal returns even in the absence of regulatory action, i.e., on non-event days.

To address this concern, I perform a simulation procedure to re-examine my results by estimating Equation (1.1) on non-event days. I randomly select four three-day event windows between 2008 and 2010 that are not overlapping, calculate the cumulative abnormal returns, and estimate the coefficients. I repeat this procedure one thousand times and retain the coefficients from each iteration. I test whether the non-event coefficients are significantly different from the event coefficients, using the distribution of the one thousand non-event coefficients. This procedure enables me to confirm whether the effects on abnormal returns are specific to the events. For my results to be unbiased, I expect that *POS CUM OCR* on non-event days is significantly different from *POS CUM OCR* on event days.

1.5. Empirical Results

1.5.1. Overall Market Reactions

In my first set of tests, I establish the overall market reactions during the major steps towards the new regulations for FVOL under IFRS 9. Table 1.4 presents descriptive portfolio raw returns and abnormal returns by event and aggregated for three different event-windows.

The first column for each event-window (Raw returns) reports unadjusted raw returns from the equally-weighted portfolio of IFRS-banks. The portfolio raw returns by event do not show a clear trend towards a positive or negative market reaction as six portfolio returns are positive and six returns are negative. On an aggregate level, I find one raw return to be below zero (-1.1%) and two being above zero (5.9% and 3.9%, respectively).

Using the STOXX GLOBAL 3000 Banks (*sg3000b*) and the STOXX Global 1800 ex North America index (*sg1800exna*) to market adjust raw returns, portfolio returns during Event #1 tend more towards a negative market reaction with two out of six CARs being significantly negative and all six CARs showing a negative sign. During Event #2, Event #3, and Event #4, CARs do not show a clear trend of either a positive or negative market reaction. On an aggregate level, two CCARs show significantly negative market reaction (-1.5% and -3.8%). In addition, five CCARs out of six exhibit a negative sign.

The results suggest that the issuance of the discussion paper (Event #1) led investors to generally adjust the value of the sample banks downwards. On an aggregate level, the market reactions tend to be slightly negative. Negative market reactions are in line with investors viewing banks that accumulated an OCR net gain as overvalued at the time of the events, as the mean of OCR net gains and losses in the sample is positive.

1.5.2. Descriptive Abnormal Returns

I reduce the sample to observations from countries in which at least one bank discloses OCR gains and losses in the financial statement notes (12 countries). In these countries, I focus on bank-observations that make use of the fair value option for financial liabilities. This approach produces 116 bank-event observations. I separately calculate the mean abnormal returns for banks that do not disclose OCR gains and losses (*Non-Disclosure*), banks that accumulated an OCR net gain since 2006 (*Pos Cum OCR*), and banks that accumulated an OCR net loss since 2006 (*Neg Cum OCR*). Then I calculate the difference in mean abnormal returns between *Pos Cum OCR* and *Neg Cum OCR*. The comparison of the mean abnormal returns is conducted for both the STOXX Global 1800 ex North America index and STOXX GLOBAL 3000 Banks index.

The nature of the results in Table 1.5 are descriptive and suggest that abnormal returns are larger for banks that accumulated an OCR net loss compared to banks that accumulated an OCR net gain (-0.8% and -1.5%, respectively). However, only the difference using the STOXX GLOBAL 3000 Banks index is significantly different from zero (-1.5%). In addition, firms that do not disclose OCR gains and losses exhibit the lowest abnormal returns of the three groups suggesting that these banks were perceived by investors as most overvalued prior to the events.

1.5.3. Cross-Sectional Analysis

The cross-sectional analysis is conducted using the multivariate regression model in Equation (1.1) and a sample consisting of OCR recognizers. Table 1.6 presents the coefficient estimates including control variables and fixed effects using different model specifications. Model (1a) – (1d) use the STOXX Global 1800 ex North America index as benchmark and Model (2a) – (2d) use the STOXX GLOBAL 3000 Banks index. All t-statistics are calculated using White (1980) heteroscedasticity-consistent standard errors except for Model (1b) and (2b), which use country-clustered heteroscedasticity-consistent standard errors.

The negative relation between abnormal returns and the dichotomous variable *POS CUM OCR* is significant for all model specifications at the 10% level (two-sided) or above. The results suggest that banks that accumulated an OCR net gain reacted significantly more negative to the events than banks that accumulated an OCR net loss. The marginal effect of *POS CUM OCR* ranges from -1.5% to -2.0%. Untabulated results show that the coefficient estimate remains significantly negative even after winsorizing the sample at the top and bottom 5% of abnormal returns. Adjusted R^2 range from 35% to 44%, which suggests a good model fit. The model fit is in line with other research that use similar methodology and sample size (e.g. Hitz and Müller-Bloch, 2015). Such high adjusted R^2 are obtained in large part from the substantial variation in event-specific abnormal returns captured by the event-fixed effects.

Control variables that turn out significant are *p/b*, *TIER 1*, and *std*. The coefficients indicate that banks with higher price-to-book ratios, below-median tier 1 capital ratios, and banks with higher stock return volatility react more positively to the events. Interpreting those control variables is difficult because there is no obvious argumentation that would explain the association between the events and the variables. However, they might control for confounding events or capture some sort of underlying trend unrelated to IFRS 9.

Further tests are conducted exploiting variation in the information environments. First, I focus on country-specific variation in the information environments by conducting the regression separately for market-based and bank-based information environment. Second, I focus on company-specific variation in information environments where I differentiate between above-median analysts following (high analysts) and below-median analysts following (low analysts) following. Table 1.7 presents the regression results.

The results suggest that the negative association between banks that accumulated an OCR net gain and abnormal returns is only present in low information environments. In market-based economies the magnitude of *POS CUM OCR* is very close to zero (-0.1% and 0.1%, respectively) whereas the magnitude in bank-based economies is larger (-3.1% and -3.2%, respectively) and statistically significant. Differentiating between information environments on a company level, I find that the magnitude of the effect is similar for high-analyst (-2.0% and -1.5%, respectively) and low-analyst banks (-2.4% and -2.3%, respectively). However, the coefficients are only significant for low-analyst banks.

Overall, the results are in line with the notion that market inefficiencies are more pronounced in low information environments. More specifically, investors assessed that banks that accumulated an OCR net gain are overpriced relative to banks that accumulated an OCR net loss. This led to more negative market reactions for banks that accumulated an OCR net gain relative to banks that accumulated an OCR net loss.

1.5.4. Monte Carlo Simulation

The results of the Monte Carlo simulations appear in Table 1.8. I present estimation coefficients from Table 1.6 Model (1c) and (2c) under β and the average coefficients resulting from the same regression on four randomly selected three-days non-event windows repeated one thousand times under $E[\beta]$. Then I test whether the average simulated coefficients $E[\beta]$ are significantly different from the cross-sectional estimated coefficients β. The results show that the coefficients on *POS CUM OCR* (-1.6%) are significantly different from the simulated coefficients on non-event days (0.3%) at the 1% level.

In addition, the significant coefficients for the control variables *p/b* and *std* are significantly different from the simulated coefficients. However, the simulated coefficients for *TIER 1* are not significantly different from the estimated coefficients, which might point to an underlying trend. That trend might be related to the financial crisis, which occurred around the time of my events, which decreased stock prices drastically. With the decrease in stock prices, banks became much more vulnerable to economic shocks. However, I can rule out a mechanical relation between *TIER 1* and *POS CUM OCR*, that might have influenced the association between abnormal returns and *POS CUM OCR*. BIS (2005) mandates that OCR gains and losses should be excluded from regulatory capital. Untabulated statistics exhibit that all simulated non-event coefficients are not significantly different from zero. This alleviates the issue of an underlying trend by suggesting that the trend between abnormal returns and *TIER 1* is weak.

Overall, the result in Table 1.8 suggest that the variation in abnormal returns that is explained by the variation in *POS CUM OCR* is unique to the event days and, therefore, is likely be driven by the new regulations for FVOL under IFRS 9 rather than misspecification or omitted variables of the cross-sectional abnormal returns.

1.6. Additional Analysis

1.6.1. Continuous Measurement

I continue to examine whether the magnitude of the OCR net gain or loss is associated with the market reactions. Table 1.9 reports coefficient estimates from Equation (1.1) replacing the dichotomous variable *POS CUM OCR* by a continuous measure *cum ocr,* defined as the accumulated OCR net gain or loss divided by the average total liabilities summed over the periods from 2006 to the year of the event date.

The coefficient estimates are very close to the full-sample results. Four coefficients, *cum ocr*, *p/b*, *TIER 1,* and *std* are significantly different from zero in at least one model specification. The coefficient estimates for *cum ocr* remain negative in all eight models but become weaker and fall below the 10% significance level in Model (2a), (2c), and (2d).

The results confirm previous results that show that there is a negative association between abnormal returns and the sign of the accumulated OCR net gain or loss. However, the association is weaker for the continuous measure than for the dichotomous variable, which is at least partly driven by the limited sample size.

1.6.2. *Small Sample Regression*

Lastly, I perform the main regressions on a subsample comprising only of banks from Germany, Italy, Switzerland, or the UK. I focus on these countries to minimize country-specific variation that are unrelated to the new regulations for FVOL under IFRS 9. Because 66.1% of the data on disclosure of OCR gains and losses stem from banks located in Germany, Italy, Switzerland, or the UK, 72 observations remain for the subsample analysis. Table 1.10 reports coefficient estimates from Equation (1.1) using observations from the subsample. The results are almost identical to those in the full sample. The coefficients for *POS CUM OCR* remain significant in six out of eight models and all having the expected sign. All other coefficients show the same sign as in the full sample except for *regulatory quality*. However, the coefficients for *regulatory quality* are not significantly different from zero both in the full-sample and in the subsample analysis.

The results suggest that banks that accumulated an OCR net gain since 2006 reacted with abnormal returns that are 1.8% to 2.2% lower than abnormal returns for banks that accumulated an OCR net loss, which is very similar to the findings in the full sample. These results should mitigate concerns that results are somehow driven by effects that are specific to countries where OCR data is sparse.

1.7. Conclusion

This study investigates market reactions to the new regulations for FVOL under IFRS 9. Previous research has shown that accounting stakeholders find it difficult to identify OCR gains and losses in financial statements and to interpret those results properly. I argue that difficulties in processing OCR information have influenced investors' assessment of firm value before the development of new standards on financial liabilities started. Due to the increased information flow from the IASB to the public during the development of IFRS 9, investors were reminded about those underlying difficulties and were able to react and reassess their valuations of banks with disclosed OCR gains and losses. These adjustments should induce market reactions during the issuance of the IFRS 9 pronouncements regarding the accounting treatment of FVOL. I further argue that market reactions are likely to depend on the information environment surrounding the banks.

In my cross-sectional regressions, I observe that banks that accumulated an OCR net gain showed significantly lower abnormal returns than banks that accumulated an OCR net loss. These findings are consistent with the notion that investors believed that firms that accumulated an OCR net gain (loss) since 2006 were relatively overpriced (underpriced). The findings on the association between the sign of the accumulated OCR net gain or loss and abnormal returns are limited to low information environments and cannot be extended to high information environments. Further analysis corroborates my findings by showing that the association is not driven by country-specific effects or underlying trends that go beyond my event dates. When I introduce a continuous variable to measure the accumulated OCR net gains and losses, the regression results become weaker but remain consistent with my previous findings.

Overall, my results suggest that (1) investors follow the standard-development process and (2) differences in information environment can influence the processing of complex information in financial statements. The results are pertinent to the broader question whether market characteristics drive information processing.

References

Armstrong, C.S., Barth, M.E., Jagolinzer, A.D., and Riedl, E.J. 2010. Market reaction to the adoption of IFRS in Europe. *The Accounting Review* (85): 31–61.

Bank for International Settlements (BIS). 2005. *Supervisory guidance on the use of the fair value option by banks under International Financial Reporting Standards*. Retrieved from http://www.bis.org/publ/bcbs127.pdf.

Barth, M.E., Hodder, L.D., and Stubben, S.R. 2008. Fair value accounting for liabilities and own credit risk. *The Accounting Review* (83): 629–664.

Bebchuk, L., Cohen, A., and Ferrell, A. 2009. What matters in corporate governance? *The Review of Financial Studies* (22): 783–827.

Beck, T. and Levine, R. 2002. Industry growth and capital allocation: Does having a market- or bank-based system matter? *Journal of Financial Economics* (64): 147–180.

Core, J.E., Guay, W.R., and Rusticus, T.O. 2006. Does weak governance cause weak stock returns? An examination of firm operating performance and investors' expectation. *The Journal of Finance* (61): 655–687.

Cremers, K.J.M. and Nair, V.B. 2005. Mechanisms and equity prices. *The Journal of Finance* (60): 2859–2894.

Fiechter, P. and Novotny-Farkas, Z. 2017. The impact of the institutional environment on the value relevance of fair values. *Review of Accounting Studies* (22): 392–429.

Financial Accounting Standards Board (FASB) and International Accounting Standards Board (IASB). 2009. *Comment letter analysis for IASB and FASB discussion paper reducing complexity in reporting financial instruments*. Retrieved from http://www.ifrs.org/Current-Projects/IASB-Projects/Financial-Instruments-A-Replacement-of-IAS-39-Financial-Instruments-Recognitio/Phase-I-Classification-and-measurement/IASB%20meeting%20summaries%20and%20observer%20notes/Documents/FI0903jointb06Aobs.pdf.

Gaynor, L.M., McDaniel, L., and Yohn, T.L. 2011. Fair value accounting for liabilities: The role of disclosure in unraveling the counterintuitive income statement effect from credit risk changes. *Accounting, Organizations and Society* (36): 125–134.

Goh, J.C. and Ederington, L.H. 1993. Is a bond rating downgrade bad news, good news, or no news for stockholders? *The Journal of Finance* (48): 2001–2008.

Gompers, P.A., Ishii, J., and Metrick, A. 2010. Extreme governance: An analysis of dual-class firms in the United States. *The Review of Financial Studies* (23): 1051–1088.

Gormley, T.A. and Matsa, D.A. 2014. Common errors: How to (and not to) control for unobserved heterogeneity. *Review of Financial Studies* (27): 617–661.

Gow, I.D., Ormazabal, G., and Taylor, D.J. 2010. Correcting for cross-sectional and time-series dependence in accounting research. *The Accounting Review* (85): 483–512.

Hirshleifer, D. and Teoh, S.H. 2003. Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics* (36): 337–386.

Hitz, J. and Müller-Bloch, S. 2015. Market reactions to the regulation of executive compensation. *European Accounting Review* (24): 659-684.

Holthausen, R.W. and Leftwich, R.W. 1986. The effect of bond rating changes on common stock prices. *Journal of Financial Economics* (17): 57–90.

International Accounting Standards Board (IASB). 2008. *Discussion paper: Reducing complexity in reporting financial instruments*. Retrieved from http://www.ifrs.org/Current-Projects/IASB-Projects/Financial-Instruments-A-Replacement-of-IAS-39-Financial-Instruments-Recognitio/Discussion-Paper-and-Comment-Letters/Documents/DPReducingComplexity_ReportingFinancialInstruments.pdf.

International Accounting Standards Board (IASB). 2009. *Staff paper accompanying discussion paper: Credit risk in liability measurement*. Retrieved from http://www.ifrs.org/Current-Projects/IASB-Projects/Credit-Risk-in-Liability-Measurement/DP-Jun-09/Documents/CreditRiskLiabilitStaff.pdf.

International Accounting Standards Board (IASB). 2010. *Snapshot: Financial Liabilities – Classification and measurement fair value option*. Retrieved from http://www.ifrs.org/Current-Projects/IASB-Projects/Financial-Instruments-A-Replacement-of-IAS-39-Financial-Instruments-Recognitio/Phase-I-Classification-and-measurement/EDFVOMay2010/Documents/SnapshotEDFairValueOptionforFinancialLiabilities.pdf.

International Accounting Standards Board (IASB). 2013. Financial Instruments: Recognition and Measurement. International Accounting Standard 39. *International Financial Reporting Standards*. London, U.K.: IASB.

International Accounting Standards Board (IASB). 2014a. Financial Instruments: Disclosures. International Financial Reporting Standard 7. *International Financial Reporting Standards*. London, U.K.: IASB.

International Accounting Standards Board (IASB). 2014b. Financial Instruments. International Financial Reporting Standard 9. *International Financial Reporting Standards*. London, U.K.: IASB.

International Accounting Standards Board (IASB). 2014c. *Project summary: IFRS 9 – Financial instruments*. Retrieved from http://www.ifrs.org/Current-Projects/IASB-Projects/Financial-Instruments-A-Replacement-of-IAS-39-Financial-Instruments-Recognitio/Documents/IFRS-9-Project-Summary-July-2014.pdf.

Kaufmann, D., Kraay, A., and Mastruzzi, M. 2009. Governance matters VIII: Aggregate and individual governance indicators 1996-2008. *Working paper, World Bank*.

Lachmann, M., Stefani, U., and Wöhrmann, A. 2015. Fair value accounting for liabilities: Presentation format of credit risk changes and individual information processing. *Accounting, Organizations and Society* (41): 21–38.

Lachmann, M., Wöhrmann, A., and Wömpener, A. 2011. Acquisition and integration of fair value information on liabilities into investors' judgement. *Review of Accounting and Finance* (10): 385–410.

Larcker, D.F., Ormazabal G., and Taylor, D.J. 2011. The market reaction to corporate governance regulation. *Journal of Financial Economics* (101): 431–448.

Lipe, R.C. 2002. Fair valuing debt turns deteriorating credit quality into positive signals for Boston Chicken. *Accounting Horizons* (16): 169-181.

MacKinlay C.A. 1997. Event studies in economics and finance. *Journal of Economic Literature* (35): 13–39.

Maffett, M. 2012. Financial reporting opacity and informed trading by international institutional investors. *Journal of Accounting and Economics* (54): 201–220.

Petersen, M.A. 2009. Estimating standard errors in finance panel data set: Comparing approaches. *Review of Financial Studies* (22): 435–480.

Sefcik S.E. and Thompson R. 1986. An approach to statistical inference in cross-sectional models with security abnormal returns as dependent variable. *Journal of Accounting Research* (24): 316–334.

Strong, J.S. 1990. Valuation effects of holding gains in long-term debt. *Journal of Accounting and Economics* (13): 267–283.

White, H. 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica* (48): 817–838.

Tables

Table 1.1: Timing and Description of Events

Event number	Event date	Form	Description
1	MAR 19, 2008	Discussion Paper: Reducing Complexity in Reporting Financial Instruments	Initiate the process of developing new standards for financial instruments. Propose that OCR gains and losses can be presented in net income, OCI, or split between the two.
2	JUN 18, 2009	Discussion Paper: Credit Risk in Liability Measurement	Seeking comments on three possible approaches to FVOL measurement. All approaches excluded OCR gains and losses from net income.
3	MAY 11, 2010	Exposure draft: Fair Value Option for financial liabilities	All three approaches were abandoned for a less complex approach that puts all OCR gains and losses in OCI unless such treatment would create or enlarge an accounting mismatch in profit and loss.
4	SEPT 28, 2010	IFRS 9: Financial Instruments	Finalization of IFRS 9 relating to the classification and measurement of financial instruments.

Table 1.2: Sample Selection Process

		Total		Observations by event			
Sample selection Process		No of banks total	No of obs. total	No of banks event 1	No of banks event 2	No of banks event 3	No of banks event 4
=	**Global IFRS banks (Bankscope)**	**5,109**					
-	Inactive	(1,174)					
-	Non-commercial and non-saving banks	(2,021)					
-	Non-ultimate owners	(1,566)					
-	Located in North or South America	(13)					
=	**Sample before data collection**	**335**					
-	Not listed	(126)					
-	No share price movements during more than 20% of trading days	(39)					
-	No share price movement during any of the events	(8)					
=	**Sample for event study**	**162**	**648**	**162**	**162**	**162**	**162**
-	Missing data on the explanatory variables	(11)	(108)	(41)	(23)	(22)	(22)
-	Confounding events	(0)	(34)	(5)	(2)	(24)	(3)
=	**Global sample**	**151**	**506**	**116**	**137**	**116**	**137**
-	Observations in non-OCR-recognizer countries	(88)	(310)	(70)	(78)	(78)	(84)
=	**Sample in OCR-recognizer countries**	**63**	**196**	**46**	**59**	**38**	**53**
-	Non-OCR recognizers	(28)	(87)	(22)	(27)	(15)	(23)
=	**Sample of OCR recognizers**	**35**	**109**	**24**	**32**	**23**	**30**

This table outlines the sample selection process. The initial IFRS sample, consisting of 5,109 banks, is extracted from Bankscope. I eliminate all inactive banks (-1,174), non-commercial banks and non-saving banks (-2,021), banks that are controlled by another company (-1,566), and banks located in North or South America (-13). For this sample, I collected data on stock returns and further eliminate companies from the sample that are not listed (-126), companies with no share price movements during more than 20% of all trading days between 2007 and 2010 (-39), and companies with missing share prices during all event windows (-8). This procedure yields an international sample of 162 banks, each having 4 event windows. I drop observations because of missing data in Thomson Reuters Eikon (-108) and because of confounding earnings releases or annual meetings (-34). The sample available for empirical tests comprises of 506 observations from 151 banks in 35 countries. Of those observations, 196 observations from 63 banks can be observed in 12 countries where OCR-recognizers are present. The sample of OCR-recognizers comprises of 109 observations from 35 banks in 12 countries.

Table 1.3: Descriptive Statistics

Panel A: Distributional statistics

Variable	FVOL users (n=178) Mean	Median	Std	Non-FVOL users (n=328) Mean	Median	Std	Combined (n=506) Mean	Median	Std
Abnormal returns:									
ar_exna_3	0.004	-0.003	0.042	-0.006	-0.004	0.038	-0.003	-0.004	0.040
ar_banks_3	-0.005	-0.007	0.041	-0.008	-0.004	0.039	-0.007	-0.005	0.040
Fair value option:									
FVOL	1.000	1.000	0.000	0.000	0.000	0.000	0.352	0.000	0.478
OCR	0.612	1.000	0.489	0.000	0.000	0.000	0.215	0.000	0.412
POS CUM OCR	0.343	0.000	0.476	0.000	0.000	0.000	0.121	0.000	0.326
cum ocr	0.710	0.000	2.800	0.000	0.000	0.000	0.250	0.000	1.692
Firm characteristics:									
size	25.919	26.152	1.974	23.069	23.171	1.728	24.072	23.807	2.270
roa	0.005	0.004	0.009	0.008	0.008	0.016	0.007	0.006	0.014
p/b	1.001	0.834	0.646	1.383	1.161	0.999	1.248	1.051	0.909
lev	18.324	15.675	9.726	10.713	8.157	7.840	13.391	11.648	9.284
TIER 1	10.892	10.020	3.572	14.747	13.200	7.031	13.391	11.800	6.315
Stock characteristics:									
chs	0.248	0.186	0.273	0.411	0.430	0.361	0.354	0.290	0.311
CL	0.607	1.000	0.490	0.073	0.000	0.261	0.261	0.000	0.440
std	0.030	0.027	0.013	0.028	0.023	0.042	0.029	0.024	0.035
spread	0.002	0.001	0.004	0.005	0.003	0.006	0.004	0.002	0.006
Environment characteristics:									
regulatory quality	1.253	1.340	0.553	0.702	0.660	0.716	0.896	0.950	0.713

Panel B: Country composition

Country	Unique firms	Firm-events	Non-FVOL users	FVOL users	OCR recognizers	ar_exna_3	ar_banks_3	Information environment	Financial structure	Regulatory quality
Australia	1	4	0	4	0	0.018	0.014	1.06		1.78
Austria	2	4	0	4	3	-0.005	-0.017	-1.06	Bank-based	1.64
Belgium	2	4	0	4	4	-0.030	-0.025	0.35	Bank-based	1.48
China	4	12	3	9	0	-0.015	-0.021	NA		-0.22
Croatia	2	8	8	0	0	-0.018	-0.020	-0.88		0.50
Cyprus	2	6	6	0	0	-0.014	-0.014	-0.76		1.25
Denmark	10	39	28	11	0	-0.006	-0.007	0.67		1.86
Egypt	1	3	3	0	0	-0.009	-0.008	0.00		-0.17
Finland	2	8	4	4	4	0.019	0.014	1.53	Market-based	1.58
France	4	8	2	6	6	0.011	0.010	0.72	Market-based	1.25
Germany	11	32	20	12	12	-0.011	-0.020	0.17	Bank-based	1.46
Greece	5	15	12	3	0	-0.011	-0.011	0.79		0.81
Hungary	2	4	4	0	0	-0.033	-0.050	0.50		1.26
Ireland	2	6	4	2	2	0.046	0.028	0.38	Bank-based	1.91
Italy	20	67	38	29	27	-0.007	-0.012	0.46	Bank-based	0.95
Jordan	8	31	31	0	0	-0.010	-0.009	0.54		0.34
Kenya	6	9	7	2	0	-0.002	-0.001	-0.39		-0.07
Kuwait	5	14	14	0	0	0.013	0.013	1.36		0.04
Malaysia	1	3	3	0	0	0.002	0.006	1.06		0.27
Norway	6	21	15	6	0	-0.014	-0.014	0.47		1.34
Oman	3	12	12	0	0	0.004	0.005	0.05		0.65
Pakistan	5	20	20	0	0	-0.005	-0.005	0.82		-0.47
Palistinia	1	2	2	0	0	0.018	0.019	NA		-1.12
Philippines	1	4	4	0	0	0.018	0.018	0.95		-0.05
Portugal	2	6	0	6	6	0.035	0.034	-0.24	Bank-based	1.12
Qatar	5	20	20	0	0	-0.014	-0.015	NA		0.66
Russia	3	12	12	0	0	-0.009	-0.019	0.99		-0.56
Saudi Arabia	7	28	24	4	0	-0.016	-0.014	1.24		0.17
South Africa	1	4	0	4	4	0.032	0.027	1.62	Market-based	0.63
Spain	5	20	4	16	0	0.027	0.014	0.85		1.27
Sweden	4	15	3	12	8	-0.005	-0.018	1.68	Market-based	1.68
Switzerland	4	16	4	12	12	0.000	-0.010	1.36	Market-based	1.66
Turkey	1	4	4	0	0	0.018	0.008	1.57		0.22
UAE	5	19	12	7	0	-0.001	0.000	NA		0.56
UK	8	26	5	21	21	0.010	-0.010	1.16	Market-based	1.79
Total (Average)	151	506	328	178	109	(-.003)	(-.007)	0.69		0.78

Panel C: Pearson Correlation

	ar_exNA_3	*ar_banks_3*	*POS CUM OCR*	*cum ocr*	*size*	*roa*	*p/b*	*lev*	*Tier 1*	*chs*	*CL*	*std*	*spread*	*regulatory quality*
Abnormal returns:														
ar_exna_3	1.000	0.903	0.002	-0.051	0.080	-0.005	0.051	0.096	-0.053	-0.025	0.065	-0.095	-0.137	0.060
ar_banks_3	0.925	1.000	-0.075	-0.073	-0.010	0.030	0.092	-0.003	0.033	-0.006	-0.022	-0.244	-0.139	-0.019
Fair value option:														
POS CUM OCR	-0.004	-0.128	1.000	0.622	0.127	-0.434	-0.365	0.223	-0.257	0.279	0.167	0.141	0.024	0.095
cum ocr	-0.077	-0.106	0.262	1.000	0.070	-0.356	-0.301	0.128	-0.211	0.117	0.124	0.062	-0.050	0.064
Firm characteristics:														
size	0.132	0.023	0.132	-0.057	1.000	-0.226	-0.169	0.553	-0.278	-0.215	0.713	0.249	-0.653	0.231
roa	-0.028	0.006	-0.389	-0.172	-0.096	1.000	0.478	-0.561	0.347	-0.049	-0.240	-0.346	0.168	-0.381
p/b	0.009	0.070	-0.315	-0.198	-0.154	0.148	1.000	-0.288	0.268	0.082	-0.225	-0.361	-0.013	-0.382
lev	0.120	-0.007	0.207	0.131	0.518	-0.431	-0.200	1.000	-0.462	-0.228	0.531	0.369	-0.354	0.512
TIER 1	-0.064	0.025	-0.257	-0.174	-0.254	0.307	0.165	-0.369	1.000	0.151	-0.271	-0.212	0.090	-0.179
Stock characteristics:														
chs	-0.032	-0.014	0.267	-0.031	-0.267	-0.169	0.132	-0.187	0.141	1.000	-0.188	-0.040	0.162	-0.131
CL	0.109	0.016	0.167	-0.050	0.746	-0.168	-0.205	0.467	-0.271	-0.219	1.000	0.243	-0.561	0.321
std	-0.078	-0.123	0.160	0.180	0.062	-0.405	0.262	0.202	-0.163	0.120	0.066	1.000	0.061	0.191
spread	-0.180	-0.170	-0.082	0.216	-0.438	0.055	-0.022	-0.148	0.008	0.072	-0.330	0.040	1.000	-0.143
Environment characteristics:														
regulatory quality	0.063	-0.007	0.179	0.027	0.246	-0.260	-0.358	0.375	-0.173	-0.147	0.313	0.066	-0.001	1.000

The global sample comprises of 506 firm-event observations from 151 banks in 35 countries between 2008 and 2010. The initial sample of IFRS-banks and data on U.S. cross listings is from Bankscope, financial data from Thomson Reuters Eikon, data on country-specific regulatory quality from the index by Kaufmann, Kraay, and Mastruzzi (2009), and hand-collected data on FVOL including OCR gains and losses from annual reports. Panel A shows distributional statistics for the variables used in the cross-sectional analysis, Panel B shows the distribution of IFRS-banks and firm-year observations by country for the global sample and for three different subsamples, and Panel C shows Pearson's correlations below the diagonal and Spearman's rank correlations above the diagonal for the variables used in the cross-sectional analysis. The subsample *Non-FVOL users* comprises of firm-events without FVOL, *FVOL users* comprises of firm-events with FVOL, and *OCR recognizers* comprises of firm-events with disclosure of OCR gains or losses. OCR recognizers is a subsample of the FVOL user sample. Indicator variables are labeled in capital letters. *ar_exna_3* and *ar_banks_3* are the cumulative abnormal returns of the IFRS-banks, estimated using a market model during the (-1,0,+1) event window around the four event dates related to the new regulations on financial liabilities under IFRS 9. Abnormal returns are estimated over the period from 11 to 250 days prior to the first event on March 19, 2008 using returns from the STOXX Global 1800 ex North America index for the *ar_exna_3* variable and the STOXX Global 3000 Banks index for the *ar_banks_3* variable. *FVOL* is an indicator variable equal to one if the bank has FVOL and zero otherwise. *OCR* is an indicator variable equal to one if the bank discloses OCR gains or losses and zero otherwise. *POS CUM OCR* is an indicator variable equal to one if the bank has accumulated an OCR net gain since 2006 and zero otherwise. *cum ocr* is the amount of accumulated OCR net gains or losses that a firm has accumulated since 2006 scaled by total liabilities times 1'000. *size* is the natural logarithm of total assets. *roa* is the return on assets calculated as income after tax divided by average of total assets. *p/b* is the price-to-book ratio calculated as market capitalization divided by total book value of equity. *lev* is the leverage ratio calculated as total liabilities divided by total book value of equity. *TIER 1* is an indicator variable equal to 1 if the core equity capital divided by total risk-weighted assets is above the median and zero otherwise. *chs* is the percentage of closely held shares calculated as one minus free floating shares divided by total shares outstanding. *CL* is an indicator variable equal to one if the bank's shares are cross listed in the USA and zero otherwise. *std* is the standard deviation of the stock returns during the calendar year for each bank. *spread* is the yearly median bid-ask spread calculated as the difference between the bid and ask price divided by the mid-point and measured at the end of each trading day. *regulatory quality* is the regulatory quality index by Kaufmann, Kraay, and Mastruzzi (2009) for the year 2008. *Information environment* is a measure for the financial market structure in a certain country (Fiechter and Novotny-Farkas, 2017). *Financial structure* is a dichotomous variable equal to market-based (bank-based) if the countries have at least one bank that discloses OCR gains and losses and *Information environment* is above (below) median.

Table 1.4: Overall Market Reactions

Variables	1-Day Window (t=0) Raw returns	Model (1)	Model (2)	3-Day Window (t=-1,0,+1) Raw returns	Model (3)	Model (4)	6-Day Window (t=-4,-3,-2,-1,0,+1) Raw returns	Model (5)	Model (6)
Intercept		0.000	0.000		0.000	0.000		0.000	0.000
		(0.62)	(0.13)		(0.61)	(0.12)		(0.07)	(0.42)
sg3000b		0.645 ***			0.645 ***			0.645 ***	
		(16.56)			(16.30)			(15.92)	
sg1800exna			0.772 ***			0.772 ***			0.772 ***
			(30.85)			(30.36)			(29.66)
by Event:									
Event #1	0.000	-0.003	-0.003	0.012	-0.040 ***	-0.009	0.042	-0.019 *	-0.001
		(-0.72)	(-0.62)		(-5.00)	(-1.21)		(-1.65)	(-0.10)
Event #2	0.006	-0.002	0.009 **	-0.013	-0.017 **	-0.011	-0.023	-0.015	-0.013
		(-0.53)	(2.13)		(-2.09)	(-1.57)		(-1.36)	(-1.26)
Event #3	-0.012	-0.011 **	-0.011 ***	0.067	0.014 *	0.031 ***	0.027	-0.005	0.004
		(-2.32)	(-2.60)		(1.76)	(4.32)		(-0.46)	(0.36)
Event #4	-0.004	0.001	-0.002	-0.007	0.005	-0.005	-0.006	0.005	0.008
		(0.22)	(-0.42)		(0.56)	(-0.63)		(0.43)	(0.76)
Aggregated:									
Events #1-4	-0.011	-0.015 *	-0.006	0.059	-0.038 **	0.007	0.039	-0.034	-0.002
		(-1.68)	(-0.75)		(-2.38)	(0.46)		(-1.52)	(-0.12)
R^2 (by Event)		0.7106	0.8043		0.7862	0.8554		0.8131	0.8736
Adj-R^2 (by Event)		0.7045	0.8001		0.7746	0.8475		0.7935	0.8603
N		244	244		252	252		264	264

This tables presents results from estimating the market reactions during four events related to the changes in accounting regulations for FVOL under IFRS 9. I present cumulative portfolio raw returns and cumulative portfolio abnormal returns for the event windows t=(0), t=(-1,0,+1), and t=(-4,-3,-2,-1,0,+1). The portfolio is an equally-weighted representation of all the banks in my sample that apply IFRS. Cumulative abnormal portfolio returns are calculated using the STOXX GLOBAL 3000 Banks index (*sg3000b*) and the STOXX GLOBAL 1800 ex North America index (sg1800exna). Cumulative portfolio abnormal returns are estimated using a single-factor market model. The market model parameters are estimated over the period from 11 to 250 days prior to the first event on March 19, 2008. I present all results for each of the four events separately and aggregated over all events. T-statistics in parentheses are calculated using heteroskedasticity-robust standard errors. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.1 levels (two-tailed).

Table 1.5: Descriptive Abnormal Returns

	Abnormal Return Ex North America t = (-1,0,+1)				Abnormal Return Banks t = (-1,0,+1)			
	Non-Disclosure	Pos Cum OCR	Neg Cum OCR	Diff	Non-Disclosure	Pos Cum OCR	Neg Cum OCR	Diff
	(1)	(2)	(3)	(2) - (3)	(4)	(5)	(6)	(5) - (6)
Mean	-0.012	0.001	0.009	-0.008	-0.017	-0.013 **	0.002	-0.015 *
	(-1.10)	(0.20)	(1.28)	(-0.90)	(-1.46)	(-2.51)	(0.40)	(-1.88)
N	7	67	42	109	7	67	42	109

This table presents mean abnormal returns for banks in countries in which at least one bank discloses OCR gains or losses (12 countries) and that use the fair value option for financial liabilities. Abnormal returns are calculated using the STOXX Global 1800 ex North America index and the STOXX Global 3000 Banks index and a 3-day event windows t=(-1,0,+1). Mean abnormal returns are calculated by three different groups: bank-events without disclosure of OCR gains or losses (*Non-Disclosure*); bank-events that accumulated an OCR net gain (*Pos Cum OCR*); and bank-events that accumulated an OCR net loss (*Neg Cum OCR*). In addition, the difference in abnormal returns between *Pos Cum OCR* and *Neg Cum OCR* is calculated. T-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tailed), respectively.

Table 1.6: Cross-Sectional Regression

	Abnormal Return Ex North America t = (-1,0,+1)				Abnormal Return Banks t = (-1,0,+1)			
Variables	Model (1a)	Model (1b)	Model (1c)	Model (1d)	Model (2a)	Model (2b)	Model (2c)	Model (2d)
Intercept	-0.026 (-0.43)	-0.026 (-0.90)	-0.023 (-0.27)	-0.059 (-0.23)	0.010 (0.17)	0.010 (0.28)	-0.007 (-0.09)	-0.077 (-0.26)
POS CUM OCR	**-0.019 ** (-2.55)**	**-0.019 *** (-3.16)**	**-0.016 ** (-2.19)**	**-0.015 * (-1.90)**	**-0.020 *** (-2.67)**	**-0.020 *** (-2.86)**	**-0.016 ** (-2.08)**	**-0.015 * (-1.77)**
size	0.001 (0.35)	0.001 (0.61)	0.000 (0.06)	-0.002 (-0.26)	-0.002 (-0.88)	-0.002 (-1.40)	-0.003 (-0.96)	-0.000 (-0.05)
roa	-0.242 (-0.54)	-0.242 (-0.32)	-0.547 (-1.34)	-0.356 (-0.83)	-0.091 (-0.21)	-0.091 (-0.11)	-0.380 (-0.95)	-0.303 (-0.72)
p/b	0.012 (1.61)	0.012 (1.54)	0.027 * (1.91)	0.031 ** (2.04)	0.012 (1.50)	0.012 (1.55)	0.035 ** (2.34)	0.035 ** (2.22)
TIER 1	-0.014 ** (-2.29)	-0.014 *** (-2.66)	-0.022 ** (-2.05)	-0.022 * (-1.93)	-0.014 ** (-2.06)	-0.014 *** (-2.71)	-0.021 * (-1.92)	-0.019 * (-1.69)
std	0.625 ** (2.31)	0.625 * (1.84)	0.861 * (1.74)	0.954 ** (2.16)	0.442 * (1.79)	0.442 (1.46)	0.792 * (1.70)	0.776 * (1.66)
lev				0.001 (1.27)				0.000 (0.33)
chs				0.004 (0.31)				-0.000 (-0.01)
CL				-0.008 (-0.38)				-0.012 (-0.54)
spread				-2.222 (-0.81)				0.276 (0.10)
regulatory quality				0.039 (0.26)				0.009 (0.05)
Event-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Clustered standard errors	No	Country	No	No	No	Country	No	No
R^2	0.44	0.44	0.54	0.56	0.41	0.41	0.51	0.51
Adj-R^2	0.39	0.39	0.43	0.44	0.35	0.35	0.40	0.37
N	109	109	109	109	109	109	109	109

This table presents OLS coefficient estimates and, in parentheses, t-statistics from a regression of abnormal returns during four 3-day event windows t=(-1,0,+1) calculated using the STOXX Global 1800 ex North America index and the STOXX Global 3000 Bank index on an indicator variable for bank-events that accumulated an OCR net gain since 2006 (*POS CUM OCR*) and control variables. *size* is the natural logarithm of total assets. *roa* is the return on assets. *p/b* is the price-to-book ratio. *TIER 1* is an indicator variable equal to 1 if the core equity capital divided by total risk-weighted assets is above median and zero otherwise. *std* is the standard deviation of the daily stock returns for each year. *lev* is the leverage ratio defined as total liabilities divided by total equity. *chs* is the percentage of closely held shares calculated as one minus free floating shares divided by total shares outstanding. *CL* is an indicator variable equal to one if the bank's shares are cross listed in the USA and zero otherwise. *spread* is the yearly median quoted spread, i.e., the difference between the bid and ask price divided by the mid-point and measured at the end of each trading day. *regulatory quality* is the regulatory quality index by Kaufmann, Kraay, and Mastruzzi (2009) for the year 2008. T-statistics are calculated using heteroskedasticity-robust standard errors (clustered by country in model b). ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tailed), respectively.

Table 1.7: Cross-Sectional Differences by Information Environments

	Country-specific				Company-specific			
	Abnormal Return Ex North America t = (-1,0,+1)		Abnormal Return Banks t = (-1,0,+1)		Abnormal Return Ex North America t = (-1,0,+1)		Abnormal Return Banks t = (-1,0,+1)	
Variables	Market-based	Bank-based	Market-based	Bank-based	High Analysts	Low Analysts	High Analysts	Low Analysts
Intercept	-0.519 *	-0.148	-0.578 *	-0.163	0.530 *	-0.124	0.505	-0.008
	(-1.89)	(-0.51)	(-1.72)	(-0.56)	(-1.65)	(-0.69)	(-1.61)	(-0.04)
POS CUM OCR	**-0.001**	**-0.031 ****	**0.001**	**-0.032 ****	**-0.020**	**-0.024 ****	**-0.015**	**-0.023 ****
	(-0.07)	**(-2.10)**	**(0.13)**	**(-2.05)**	**(-0.87)**	**(-2.32)**	**(-0.63)**	**(-2.17)**
size	-0.009	0.005	-0.007	0.004	-0.029 *	0.012	-0.027 *	0.010
	(-1.08)	(0.39)	(-0.75)	(0.35)	(-1.91)	(1.18)	(-1.67)	(0.95)
roa	-0.540	-0.942	-0.533	-0.902	-3.041	-0.671	-2.679	-0.676
	(-1.20)	(-0.34)	(-1.19)	(-0.31)	(-0.92)	(-1.12)	(-0.80)	(-1.14)
p/b	0.030	0.021	0.030	0.033	0.002	0.000	0.001	0.004
	(1.46)	(0.51)	(1.37)	(0.72)	(0.08)	(0.01)	(0.03)	(0.12)
TIER 1	-0.009	-0.051	-0.008	-0.056	-0.038 *	-0.015	-0.033	-0.019
	(-0.84)	(-0.73)	(-0.69)	(-0.75)	(-1.73)	(-0.85)	(-1.31)	(-1.00)
std	1.040 **	0.569	0.998 *	0.125	0.457	0.521	0.386	0.179
	(2.20)	(0.76)	(1.92)	(0.16)	(0.77)	(0.73)	(0.60)	(0.22)
lev	0.001	0.000	0.000	0.000	0.001	-0.001	0.000	-0.001 *
	(1.16)	(0.02)	(0.06)	(0.45)	(1.09)	(-1.45)	(0.34)	(-1.78)
chs	-0.034	0.025	-0.044 *	0.015	-0.068	0.007	-0.071	0.007
	(-1.64)	(0.89)	(-1.91)	(0.54)	(-1.09)	(0.47)	(-1.09)	(0.43)
CL	0.011	-0.022	0.007	-0.017	0.006	-0.050 *	-0.026	-0.043
	(0.36)	(-0.62)	(0.20)	(-0.48)	(0.11)	(-1.69)	(-0.43)	(-1.41)
spread	0.121	-4.119	2.667	-1.469	-22.393 *	-0.862	-24.196 *	1.442
	(0.09)	(-0.83)	(1.44)	(-0.27)	(-1.70)	(-0.34)	(-1.74)	(0.54)
regulatory quality	0.400 **	0.024	0.386 *	0.024	0.176	-0.072	0.158	-0.130
	(2.31)	(0.49)	(1.84)	(0.43)	(0.82)	(-0.93)	(0.65)	(-1.47)
Event-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered standard errors	No	No	No	No	No	No	No	No
R^2	0.67	0.65	0.56	0.65	0.65	0.64	0.59	0.62
Adj-R^2	0.52	0.45	0.35	0.45	0.39	0.45	0.29	0.42
N	57	48	57	48	44	65	44	65

This table presents OLS coefficient estimates and, in parentheses, t-statistics from a regression of abnormal returns during four 3-day event windows t=(-1,0,+1) calculated using the STOXX Global 1800 ex North America index and the STOXX Global 3000 Bank index on an indicator variable for bank-events that accumulated an OCR net gain since 2006 (*POS CUM OCR*) and control variables. The first four column present regression results, splitting the sample into market-based and bank-based economies depending on the country of the bank's headquarters. Following Beck and Levine (2002) and Fiechter and Novotny-Farkas (2017), I categorize countries with above (below) median values of the first principal component of two variables that measure the comparative activity and size of the banking industry relative to the stock markets as market-based (bank-based) economies. The last four column present regression results separately for banks with above-median and below-median analyst following. *size* is the natural logarithm of total assets. *roa* is the return on assets. *p/b* is the price-to-book ratio. *TIER 1* is an indicator variable equal to 1 if the core equity capital divided by total risk-weighted assets is above median and zero otherwise. *std* is the standard deviation of the daily stock returns during for each year. *lev* is the leverage ratio defined here as total liabilities divided by total equity. *chs* is the percentage of closely held shares calculated as one minus free floating shares divided by total shares outstanding. *CL* is an indicator variable equal to one if the bank's shares are cross listed in the USA and zero otherwise. *spread* is the yearly median quoted spread, i.e., the difference between the bid and ask price divided by the mid-point and measured at the end of each trading day. *regulatory quality* is the regulatory quality index by Kaufmann, Kraay, and Mastruzzi (2009) for the year 2008. T-statistics are calculated using heteroskedasticity-robust standard errors (clustered by country in model b). ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tailed), respectively.

Table 1.8: Monte Carlo Simulations

	Abnormal Return Ex North America t = (-1,0,+1)			Abnormal Return Banks t = (-1,0,+1)		
Variables	Regression β		Monte Carlo E[β]	Regression β		Monte Carlo E[β]
Intercept	-0.023		0.023	-0.007		0.019
		(-0.54)			(-0.32)	
POS CUM OCR	**-0.016 ****		**0.003**	**-0.016 ****		**0.003**
		(-2.58) ***			**(-2.61) *****	
size	-0.000		0.000	-0.003		0.000
		(-0.02)			(-0.82)	
roa	-0.547		-0.025	-0.380		0.006
		(-1.28)			(-0.97)	
p/b	0.027 *		-0.011	0.035 **		-0.007
		(2.68) ***			(2.82) ***	
TIER 1	-0.022 **		-0.011	-0.021 *		-0.008
		(-1.02)			(-1.19)	
std	0.861 *		-0.159	-0.792 *		-0.096
		(2.06) **			(1.91) *	

This table presents results from a Monte Carlo analysis. The simulation process is as follows. First, I estimate abnormal returns using the STOXX Global 1800 ex North America index and the STOXX Global 3000 Banks index. Second, I randomly select four 3-day windows that do not overlap with the event windows during a period from January 2008 to December 2010. Third, I regress abnormal returns during the selected four event windows on an indicator variable for bank-events that accumulated an OCR net gain since 2006 (*POS CUM OCR*) and control variables. I repeat the second and third step one thousand times retaining coefficient estimates for each iteration. Fourth, I test whether the average of the one thousand estimated coefficients on non-event days (E[β]) are significantly different from the estimated coefficients on event days (β). T-statistics for the test E[β]=β appear in parentheses. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 level (two-tailed), respectively.

Table 1.9: Continuous Accumulated OCR Gains and Losses

	Abnormal Return Ex North America t = (-1,0,+1)				Abnormal Return Banks t = (-1,0,+1)			
Variables	Model (1a)	Model (1b)	Model (1c)	Model (1d)	Model (2a)	Model (2b)	Model (2c)	Model (2d)
Intercept	-0.036	-0.036	-0.047	-0.158	-0.014	-0.014	-0.038	-0.172
	(-0.61)	(-1.03)	(-0.58)	(-0.63)	(-0.24)	(-0.34)	(-0.48)	(-0.61)
cum ocr	**-0.002 ***	**-0.002 *****	**-0.002 ****	**-0.002**	**-0.001**	**-0.001 ***	**-0.001**	**-0.002**
	(-1.78)	**(-3.61)**	**(-1.98)**	**(-1.49)**	**(-1.10)**	**(-1.78)**	**(-1.28)**	**(-1.31)**
size	0.001	0.001	-0.001	-0.003	-0.002	-0.002	-0.003	-0.001
	(0.28)	(0.43)	(-0.21)	(-0.38)	(-0.74)	(-1.00)	(-1.01)	(-0.18)
roa	-0.027	-0.027	-0.296	-0.133	0.171	0.171	-0.126	-0.091
	(-0.06)	(-0.04)	(-0.65)	(-0.29)	(0.37)	(0.20)	(-0.30)	(-0.21)
p/b	0.013	0.013	0.035 ***	0.036 **	0.014 *	0.014	0.044 ***	0.040 ***
	(1.63)	(1.29)	(2.58)	(2.50)	(1.67)	(1.41)	(3.11)	(2.68)
TIER 1	-0.013 *	-0.013 **	-0.028 **	-0.023 *	-0.012 *	-0.012 **	-0.024 **	-0.021 *
	(-1.91)	(-2.15)	(-2.34)	(-1.90)	(-1.72)	(-2.06)	(-2.03)	(-1.69)
std	0.637 **	0.637 **	1.071 **	1.060 **	0.415 *	0.415	0.951 **	0.879 *
	(2.58)	(2.07)	(2.48)	(2.41)	(1.75)	(1.43)	(2.14)	(1.89)
lev				0.001				0.000
				(1.42)				(-0.45)
chs				-0.006				-0.010
				(-0.40)				(-0.67)
CL				-0.006				-0.010
				(-0.30)				(-0.45)
spread				-0.290				2.179
				(-0.13)				(0.91)
regulatory quality				0.095				0.064
				(0.67)				(0.40)
Event-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Clustered standard errors	No	Country	No	No	No	Country	No	No
R^2	0.43	0.43	0.54	0.56	0.37	0.37	0.50	0.51
Adj-R^2	0.37	0.37	0.44	0.44	0.31	0.31	0.39	0.38
N	109	109	109	109	109	109	109	109

This table presents OLS coefficient estimates and, in parentheses, t-statistics from a regression of abnormal returns during four 3-day event windows t=(-1,0,+1) calculated using the STOXX Global 1800 ex North America index and the STOXX Global 3000 Bank index on a continuous measure of accumulated OCR gains and losses (*cum ocr*) and control variables. *size* is the natural logarithm of total assets. *roa* is the return on assets. *p/b* is the price-to-book ratio. *TIER 1* is an indicator variable equal to 1 if the core equity capital divided by total risk-weighted assets is above median and zero otherwise. *std* is the standard deviation of the daily stock returns during for each year. *lev* is the leverage ratio defined here as total liabilities divided by total equity. *chs* is the percentage of closely held shares calculated as one minus free floating shares divided by total shares outstanding. *CL* is an indicator variable equal to one if the bank's shares are cross listed in the USA and zero otherwise. *spread* is the yearly median quoted spread, i.e., the difference between the bid and ask price divided by the mid-point and measured at the end of each trading day. *regulatory quality* is the regulatory quality index by Kaufmann, Kraay, and Mastruzzi (2009) for the year 2008. T-statistics in parentheses are calculated using heteroskedasticity-robust standard errors (clustered by country in model b). ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tailed), respectively.

Table 1.10: Small Sample Cross-Sectional Regression (ITA, UK, CH, and GER)

	Abnormal Return Ex North America t = (-1,0,+1)				Abnormal Return Banks t = (-1,0,+1)			
Variables	Model (1a)	Model (1b)	Model (1c)	Model (1d)	Model (2a)	Model (2b)	Model (2c)	Model (2d)
Intercept	-0.048	-0.048	-0.015	0.137	-0.009	-0.009	0.010	0.066
	(-0.68)	(-1.38)	(-0.17)	(0.80)	(-0.13)	(-0.22)	(0.12)	(0.37)
POS CUM OCR	**-0.018**	**-0.018 ****	**-0.018 ***	**-0.022 ***	**-0.020 ***	**-0.020 ***	**-0.019 ***	**-0.019**
	(-1.63)	**(-2.02)**	**(-1.76)**	**(-1.74)**	**(-1.78)**	**(-1.88)**	**(-1.85)**	**(-1.45)**
size	0.001	0.001	0.000	-0.004	-0.002	-0.002	-0.002	-0.000
	(0.41)	(0.52)	(0.09)	(-0.46)	(-0.68)	(-0.94)	(-0.81)	(-0.05)
roa	-0.695	-0.695	-0.796 *	-0.572	-0.577	-0.577	-0.647	-0.538
	(-1.54)	(-1.19)	(-1.91)	(-1.32)	(-1.37)	(-0.97)	(-1.64)	(-1.29)
p/b	0.025 *	0.025	0.030 *	0.035 *	0.025 *	0.025 *	0.037 **	0.039 **
	(1.85)	(1.64)	(1.73)	(1.95)	(1.81)	(1.73)	(2.04)	(2.06)
TIER 1	-0.018 **	-0.018	-0.028 *	-0.032 *	-0.019 *	-0.019	-0.025	-0.028
	(-1.97)	(-1.37)	(-1.80)	(-1.85)	(-1.86)	(-1.52)	(-1.61)	(-1.61)
std	0.847 **	0.847	0.851	1.077 **	0.630 *	0.630	0.821	0.943 *
	(2.28)	(1.38)	(1.51)	(2.23)	(1.90)	(1.15)	(1.55)	(1.85)
lev				0.001				0.000
				(1.39)				(0.34)
chs				0.013				0.004
				(0.81)				(0.20)
CL				-0.008				-0.017
				(-0.31)				(-0.61)
spread				-5.348 **				-2.831
				(-2.20)				(-1.00)
regulatory quality				-0.043				-0.067
				(-0.71)				(-1.01)
Event-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Clustered standard errors	No	Country	No	No	No	Country	No	No
R^2	0.40	40.00	0.43	0.43	0.38	0.38	0.41	0.43
Adj-R^2	0.32	0.32	0.31	0.31	0.29	0.29	0.29	0.26
N	72	72	72	72	72	72	72	72

This table presents OLS coefficient estimates and, in parentheses, t-statistics from a regression of abnormal returns during four 3-day event windows t=(-1,0,+1) calculated using the STOXX Global 1800 ex North America index and the STOXX Global 3000 Bank index on an indicator variable for bank-events that accumulated an OCR net gain since 2006 (*POS CUM OCR*) and control variables. We use a subsample comprising only of banks located in Italy, Germany, Switzerland, or the U.K. *size* is the natural logarithm of total assets. *roa* is the return on assets. *p/b* is the price-to-book ratio. *TIER* 1 is an indicator variable equal to 1 if the core equity capital divided by total risk-weighted assets is above median and zero otherwise. *std* is the standard deviation of the daily stock returns for each year. *lev* is the leverage ratio defined as total liabilities divided by total equity. *chs* is the percentage of closely held shares calculated as one minus free floating shares divided by total shares outstanding. *CL* is an indicator variable equal to one if the bank's shares are cross listed in the USA and zero otherwise. *spread* is the yearly median quoted spread, i.e., the difference between the bid and ask price divided by the mid-point and measured at the end of each trading day. *regulatory quality* is the regulatory quality index by Kaufmann, Kraay, and Mastruzzi (2009) for the year 2008. T-statistics are calculated using heteroskedasticity-robust standard errors (clustered by country in model b). ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tailed), respectively.

Chapter 2: The Market Perception of Own Credit Risk

(In collaboration with Peter Fiechter)

2.1. Introduction

This paper examines whether and how recognized own credit risk (OCR) gains and losses on financial liabilities designated at fair value through profit or loss (FVOL) are reflected in stock-based measures (i.e., stock returns, stock prices, and stock return volatility).[12] By providing empirical evidence on the market perception of OCR gains and losses, we aim to shed light on the long-standing debate regarding the accounting for FVOL (IASB, 2009).

On the one hand, OCR gains and losses may not be useful because changes in credit risk for FVOL are arguably counterintuitive, as an entity reports a gain (loss) from deterioration (improvement) in its credit quality. In addition, because FVOL are typically used for funding purposes and are difficult to transfer, unrealized OCR gains and losses can rarely be realized. In line with these arguments, critics claim that equity analysts and investors ignore OCR gains and losses, because they do not reflect economic performance (e.g. JP Morgan Chase, 2009; KPMG, 2009; UBS, 2009; and IASB, 2009). On the other hand, OCR gains and losses may be useful, because they convey information regarding the effective interest rate of debt and loan agreements, refinancing requirements, the wealth transfer that has occurred from bondholders to shareholders, and because OCR gains and losses may offset declines in the fair value of assets (CFA Institute, 2009 and IASB, 2009).

The relation between OCR gains and losses and stock-based measures is ex ante unclear. First, if OCR gains and losses are not useful or if OCR gains and losses are a noisy measure of an entity's own credit risk changes (e.g. Dong, Doukakis, and Ryan, 2016), we expect an insignificant association between OCR gains and losses and stock-based measures. Second, if

[12] OCR gains and losses are also referred to as debt valuation adjustments (DVA).

investors interpret OCR gains and losses as a *normal* component of net income, we expect OCR gains and losses to be positively associated with stock returns and stock prices. Third, if OCR gains and losses reflect changes in the entity-wide credit risk (i.e., the asset-side effect dominates the liability-side effect), we expect OCR gains and losses to be negatively associated with stock returns and stock prices. In addition, if OCR gains and losses are significantly related to stock returns and stock prices—regardless of the sign of the association—we expect volatility in OCR gains and losses to be positively associated with stock-based risk measures, because volatility in OCR gains and losses likely reflects banks' exposure to credit risk.

To examine the market perception of OCR gains and losses, we apply different research methodologies. We closely follow prior research by using return-relevance (Bhat and Ryan, 2015), value-relevance (e.g. Barth and Clinch, 1998; Landsman, Peasnell, and Shakespeare, 2008; and Fiechter and Novotny-Farkas, 2017), and risk-relevance (Hodder, Hopkins, and Wahlen, 2006) methodology to analyze whether OCR gains and losses are reflected in stock returns, in stock prices, and in different stock-based risk measures, respectively. We use all three relevance models to mitigate some of the concerns that come with the use of the individual models.[13]

Using an international sample of IFRS banks from 2006 to 2015 (2,298 bank-year observations), we find that OCR gains and losses are negatively related to stock returns and stock prices, respectively, indicating that the market perceives OCR gains (losses) as a negative (positive) signal for the bank's (future) economic performance. In contrast to the positive coefficient estimates for interest income, the negative coefficients for OCR gains and losses suggest that investors do *not* perceive them as a *normal* component of net income. In addition, we find that volatility in OCR gains and losses is positively related to volatility in

[13] For example, return relevance is more prone to measurement error; value relevance is more prone to omitted variable bias; and risk relevance is more prone to autocorrelation (Barth, Beaver, and Landsman, 2001; Holthausen and Watts, 2001; and Bhat and Ryan 2015).

stock returns, indicating that OCR gains and losses are risk relevant. Taken together, these findings suggest that recognized OCR gains and losses are useful for assessing the entity-wide changes in credit risk, and thus the bank's economic performance.

To mitigate concerns that less sophisticated investors interpret OCR gains and losses differently (i.e., as a *normal* income component) than more sophisticated investors, we allow for cross-sectional variation in investor sophistication. Related, we also test whether differences in the information environment affect investors' processing of OCR information. We do not find that differences in investor sophistication or different information environments affect the market perception of OCR gains and losses. In addition, to bolster our interpretation that the asset-side effect of changes in credit risk dominates the liability-side effect, we compare OCR gains and losses with proxies for credit-related asset write-downs (i.e., loan losses and changes in loan loss provisions). Consistent with our inferences from the market-based tests, we find that credit-related asset write-downs are positively correlated with, and of higher magnitude than, OCR gains and losses. Finally, we find no evidence that different levels of bank leverage affect the negative association between OCR gains and losses and stock returns.[14]

We make several contributions to the literature. First, our empirical evidence suggests that—contrary to various claims that OCR should be ignored—OCR gains (losses) signal negative (positive) economic performance. This finding further suggests that markets do *not* perceive OCR gains and losses as a *normal* component of net income. The negative association between OCR gains and losses and stock returns and stock prices, respectively, also indicates that the asset-side effect of changes in credit risk dominates the liability-side effect. We thus shed light on the discussion as to whether OCR gains and losses—if not

[14] For example, Barth, Hodder, and Stubben (2008) find that 27 percent of the downgraded firms—which are highly leveraged—recognize asset write downs smaller than unrecognized gains from the decrease in overall debt value. To mitigate concerns that our results hold only for *moderately* leveraged firms, we examine whether the association between OCR gains and losses and stock return varies with leverage. However, our sample consists of banks, which have inherently high leverage ratios (sample median = 0.91).

considered in isolation—are counterintuitive (IASB, 2009). Second, we add to Barth, Hodder, and Stubben (2008) by directly testing the relation between recognized OCR gains and losses on FVOL and stock returns; rather than testing the relation between model-based unrecognized OCR gains and losses on total debt and stock returns. Therefore, we can make inferences about the usefulness of recognized OCR gains and losses under IFRS. Third, we mitigate concerns that investors systematically misinterpret OCR gains and losses when assessing an entities economic performance, as indicated by previous experimental studies (Gaynor, McDaniel, and Yohn, 2011; Lachmann, Wöhrmann, and Wömpener, 2011; Lachmann, Stefani, and Wöhrmann, 2015).

Understanding the link between OCR gains and losses and stock-based measures is important for several reasons. First, banks are highly leveraged compared to non-financial firms. Thus, small changes in the value of liabilities may strongly impact comprehensive income and book value of equity. Second, banks are highly exposed to credit risk due to their business model. Counterparty credit risk translates, among other factors, directly into bank's own credit risk. Hence the assessment of an entity's risk exposure is crucial to understand asset, liability, and earnings fluctuations rooted in credit risk fluctuations. Third, understanding the relation between OCR gains and losses and stock-based outcomes may help policy makers in assessing *whether* and *how* OCR information should be incorporated into financial statements.

The remainder of the paper is as follows. Section 2.2 explains (a) the accounting treatment for financial liabilities under IAS 39 and IFRS 9; (b) reviews the related empirical and theoretical literature on the relation between credit risk and equity valuation as well as the related experimental literature on the processing of OCR information; and (c) describes the hypotheses development. Section 2.3 describes the research design. Section 2.4 describes the sample selection process and presents summary statistics. Section 2.5 presents the main results. Section 2.6 presents additional results and discusses robustness tests. Section 2.7 concludes.

2.2. Background and Hypotheses Development

2.2.1. Accounting Treatment for Financial Liabilities under IAS 39 and IFRS 9

At initial recognition, financial liabilities are measured at fair value plus, in the case of a financial liability measured at amortized cost, transaction costs directly attributable to the issuance of the financial liability. Subsequently, financial liabilities are measured at amortized cost except for financial liabilities classified as held for trading (HFT) and financial liabilities designated at initial recognition at fair value through profit or loss. Financial liabilities classify as HFT if they are incurred for short-term profit-taking or if they are derivatives, except for financial guarantee contracts and derivatives designated as hedging instruments. Upon recognition, financial liabilities measured at amortized cost can be designated at fair value through profit or loss if it reduces an accounting mismatch or if the financial liabilities are managed by a group on a fair value basis. A measurement inconsistency may be eliminated if, for example, a contract contains a substantial derivative component. Instead of separating the host contract from the embedded derivative, the fair value option allows the entire hybrid contract to be measured at fair value through profit or loss (IASB, 2013).

Financial liabilities that are typically designated at fair value include structured notes such as equity-linked, credit-linked, or rates-linked notes (substantive derivative component), non-structured fixed-rate bonds, the market risk of which is economically hedged by derivatives (reducing an accounting mismatch), and securities sold under repurchase agreements (managed on a fair value basis). The effect of periodical and cumulative changes in the entity's credit risk on FVOL needs to be disclosed (IASB, 2014a). An increase (decrease) in an entity's own credit risk influences the expectation of future cash flows of the underlying financial liability, thereby decreasing (increasing) the value of the financial liability, resulting in a gain (loss) recognized in net income.

As part of the convergence project between IFRS and US GAAP, the IASB and the FASB overhauled its regulations on financial instruments. In July 2014, the IASB issued its new regulations under *IFRS 9 – Financial Instruments* to the public. The IASB continues to allow designating financial liabilities at fair value (FVOL). However, standard setters changed the information location of OCR gains and losses from net income to other comprehensive income (OCI)—where it will appear as a separate line item—unless presentation in OCI introduces an accounting mismatch (IASB, 2014b). "It does make the results more understandable," said Mark LaMonte, chief credit officer of the financial institutions group at Moody's Investors Service (Rapoport, 2015). The new information location does not mean that the IASB believes that information is not useful, as the board clearly states that "[OCI items] are relevant gains and losses […] and investors should certainly take into account in their analysis the gains and losses that appear there" (Cooper, 2015). More specifically, the IASB states that they continue to allow the designation of financial liabilities, because they still deem OCR gains and losses useful (IASB, 2014c).

2.2.2. Literature Review

The credit risk component of FVOL is a measure that is available in IFRS financial statements, providing investors with information regarding an entity's own assessment of their change in credit risk. Hence our research is closely related to the literature investigating the relation between changes in credit risk and changes in market value of equity. In addition, we relate to the scarce (experimental) literature on the processing of OCR information.

2.2.2.1. *Credit Risk and Equity Valuation*

In debt valuation, there are two primary risks that might induce changes to the value of a bond price during the time to maturity. First, changes in interest rates inversely affect bond prices through opportunity costs of holding a particular bond compared to switching to another bond that reflects current interest rates (interest-rate risk). Second, changes in the probability of default of a particular bond directly affect the expectation of future cash flows—such as coupon and principal—and hence bond prices (credit risk). Credit risk changes stem either from unanticipated asset risk changes or from asset value changes (Barth, Hodder, and Stubben, 2008). Those two changes that affect the probability of a bond default are likely to affect the probability of equity default. Hence, it seems intuitive that increases in credit risk should negatively affect the market value equity. However, early studies on this association show mixed results (Ederington and Yawitz, 1987).

Strong (1990) argues that prior studies are unable to consistently find a redistribution effect of bond revaluations on stock returns, because they do not control for unanticipated changes in inflation. By disaggregating unanticipated inflation from holding gains and losses on long-term debt, Strong (1990) shows that both changes in credit risk and changes in unanticipated inflation produce significant but opposing effects on market value of debt. In addition, changes in credit risk dominate unanticipated inflation effects for investment-grade bond contracts.

More recent studies that put greater effort into the identification of concurrent important news at the time around the credit deterioration find more conclusive negative market reactions to credit rating downgrades (e.g. Griffin and Sanvicente, 1982; Wansley and Clauretie, 1985; Holthausen and Leftwich, 1986; Hand, Holthausen, and Leftwich, 1992; and Goh and Ederington, 1993). They, however, do not find significant market reactions to upgrades. Goh and Ederington (1993) point out that not all credit rating downgrades need to be bad news for shareholders. Their identification strategy is to separate downgrades due to a reevaluation of the firm's financial prospects from downgrades due to an anticipated increase in leverage (e.g. leveraged buyouts or debt-financed expansion). They argue that only the former should trigger negative market reactions, whereas the latter may induce a wealth transfer to shareholders, and thus should trigger positive market reactions. Their results then show that the former indeed triggers negative market reactions, whereas the latter does not trigger any market reactions.

Kliger and Sarig (2000) investigate Moody's refinement of its rating systems in 1982, which was not accompanied by any fundamental change in issuers' credit risk. This setting allows them to investigate whether the incremental information of the refined system exhibits incremental value relevance. They, however, find no evidence that the new rating information affects firm value and find mixed evidence on the equity implication of bond rating changes.

From a theoretical standpoint, Merton (1974) outlines the negative association between credit risk and the market value of equity by disentangling two countervailing effects—(1) the negative effect of asset value deterioration on market value of equity and (2) the negative effect of asset value deterioration on the market value of debt, increasing the market value of equity. Merton (1974) further shows that effect (1) dominates effect (2), resulting in a negative association between credit risk and the market value of equity.

To empirically investigate these two distinct effects of changes in credit risk, Barth, Hodder, and Stubben (2008) estimate credit ratings by first estimating the relation between financial statement variables and credit ratings for firms with credit ratings, and then using these coefficient estimates to calculate credit ratings for the remaining firms.[15] Barth, Hodder, and Stubben (2008) show that the negative relation between changes in market value of equity and changes in credit risk is less pronounced for firms with more debt. They interpret this

[15] A drawback of this approach is that firms with credit ratings are typically large firms, which are then used to estimate credit ratings for small firms.

finding as evidence that credit-risk-induced changes in the market value of equity are attenuated by unrecognized credit risk changes on debt.

Additional descriptive results by Barth, Hodder, and Stubben (2008) further suggest that if credit risk was only recognized in debt valuation, then firms recognize gains due to credit deteriorations. However, the results also reveal that, on average, firms with downgraded credit quality show lower net income. Although the indirect effect is, on average, dominated by the direct effect of asset value deteriorations, some concern about the counterintuitive effect is warranted because a few firms show a dominant indirect effect. Yet, whether those concerns can be transferred to a setting with recognized OCR gains and losses is not clear. In addition, whether recognized OCR gains and losses on FVOL convey useful information about overall changes in credit risk remains an open question.

2.2.2.2. Processing of OCR Information

Using Boston Chicken for his case study, Lipe (2002) shows how the measurement of financial liabilities at fair value can distort important financial ratios such as debt-to-equity, return-on-equity, and interest-coverage when facing material credit deterioration. Lipe (2002) raises concerns that the measurement asymmetry between assets and financial liabilities may produce unwarranted positive signals to investors. More recent experimental studies suggest that both professional and non-professional accounting statement users tend to misinterpret the relation between OCR gains and losses on FVOL and firms' overall default risk (Gaynor, McDaniel, and Yohn, 2011; Lachmann, Wöhrmann, and Wömpener, 2011; and Lachmann, Stefani, and Wöhrmann, 2015).

Gaynor, McDaniel, and Yohn (2011) find that more than 70% of participants (i.e., certified public accountants) incorrectly interpret firms that disclose own credit gains as less risky investments. They also find that a relational disclosure significantly improves participants' ability to properly interpret the OCR gains and losses. Their conclusions that knowledgeable financial statement users misinterpret OCR gains and losses, however, are based on the implicit assumption that OCR gains (losses) should be interpreted as a negative (positive) performance signal, although participants are not provided with information on what drives the change in credit risk, how those changes co-affect the asset-side, and whether the effect on the asset-side has already been recognized in financial statements.

Conducting an experiment with knowledgeable non-professional financial statement users, Lachmann, Wöhrmann, and Wömpener (2011) confirm previous results by showing that participants rely on additional disclosures in the notes and need to exert more cognitive effort to process OCR information, although a separate line item for OCR changes in net income is provided. In reality, however, a separate line item for OCR gains and losses is unlikely to be found in net income statements. Instead, the information has to be obtained from the notes to the financial statements, which likely further decreases the information processing ability.[16]

Lachmann, Stefani, and Wöhrmann (2015) investigate whether the location of the information on own credit risk matters. They find that the perceived importance of the information is slightly lower if presented in OCI instead of net income, and the risk of misinterpreting the directional effect of the information remains unchanged. However, they find that participants are less likely to make biased estimation of the value of the firm if OCR

[16] While collecting the data for this study, we identified several (more practical) issues regarding the disclosure of OCR information: First, isolating the OCR component of a fair value change of FVOL can be difficult, as the OCR component is usually not presented as a separate line item in income statements, but as part of trading income. Therefore, financial statement users have to screen the notes to the financial statements to obtain the appropriate information. Second, disclosures on OCR gains (losses) are heterogeneous across firms. For example, some banks present the amount as decrease (increase) in liability, some present the amount as increase (decrease) in net income, and others do not elaborate on the sign of the OCR adjustment. Third, many banks do not disclose the OCR component of a fair value change of the FVOL or they bypass the disclosure requirements by declaring that OCR has not changed substantially. Fourth, banks seem to disagree about the definition of *cumulative* changes in own credit risk. Some banks interpret the term "cumulative" as the sum of all periodical OCR gains and losses up to the current financial year end, whereas others interpret "cumulative" as the life-to-date change in FVOL due to changes in an entity's own credit risk.

gains and losses are presented in OCI than in net income. They argue that net income is inflated by deterioration in credit quality if OCR gains and losses are presented in net income, whereas net income is not inflated if OCR gains and losses are presented in OCI. This interpretation implicitly assumes that participants should neutralize OCR gains and losses for firm valuation, because OCR gains and losses do not provide useful information about the entity's performance. However, whether OCR gains and losses are useful to investors and, if so, whether they are positively or negatively associated with stock-based measures, has not been addressed by previous research.

2.2.3. Hypotheses Development

FVOL and OCR gains are losses are subject to controversial discussions among academics, regulators, financial statement users, and financial statement preparers, generating more comments during the development of IFRS 9 than any other aspect of fair value measurement (IASB, 2009). J.P. Morgan Chase CEO James Dimon, called the accounting for own credit risk as "one of the more ridiculous concepts that's ever been invented in accounting" (Rapoport, 2015). Generally, opponents of the accounting for OCR argue that reporting a profit (loss) from deterioration (improvement) in credit quality is counterintuitive and potentially misleading, masking the real economic performance of a company.

Others express their concern that financial liabilities can seldom be transferred, and thus OCR gains or losses cannot be realized. Economic restrictions, such as the requirement for permission by the counterparty, may prevent entities from prematurely exiting non-structured fixed rate bonds. In addition, as an entity with decreased credit standing likely has difficulties to find the means to close-out those bonds, realization is more hypothetical than actual. Consistent with this view, some entities claim in the comment letters to the *Discussion Paper – Credit Risk in Liability Measurement* that equity analysts and investors ignore OCR gains and losses because OCR fluctuations do not reflect economic performance (e.g. JP Morgan Chase, 2009; KPMG, 2009; and UBS, 2009). Although it is difficult to prematurely close-out bonds—especially during economic downturns—financial institutions such as Canary Wharf, Bank of Ireland, and Lloyd's of London were able to take advantage of deteriorated financial liabilities by retiring outstanding debt early at a significant discount during the financial crisis (Guider, 2009; Steiner, 2009; and Essen, 2009).

Proponents argue that consideration of changes in financial liabilities due to changes in a company's own credit risk is consistent with the initial measurement of financial liabilities, i.e., promised future proceeds are discounted by a rate that reflects the probability that borrowers will fail to pay (some of) the proceeds. Thus, OCR gains and losses convey information regarding the effective interest rate of debt and loan agreements, about refinancing requirements, and hedging costs (CFA Institute, 2009). In addition, the so-called counterintuitive effect of changes in credit risk on net income reflects the wealth transfer between debtholders and shareholders, i.e., the indirect effect in the Merton's model that attenuates the direct effect on the asset side (if measured at fair value) (Merton, 1974). Overall, proponents emphasize investors' need to assess asset, liability, and earnings quality for gains rooted in credit deterioration, allowing them to understand signals given by credit markets about an entity's future creditworthiness (CFA Institute, 2009).

Both opponents and proponents argue that changes in credit quality do not happen in a vacuum but signal a change in the value of the asset-side and that accounting mismatches should be reduced to a minimum. Opponents argue that accounting mismatches occur because assets may not be measured on a current basis (e.g. tangible assets, intangible assets, and goodwill) or may be unrecognized on the balance sheet (e.g. unrecognized intangible assets such as employee skills or internally generated brands) (Cedergren, Chen, and Chen, 2015). Proponents emphasize that the accounting mismatch can be amplified if assets are measured at fair value and financial liabilities are not. HSBC (2009) highlights that one of the main reasons for the use of FVOL is to reduce accounting mismatches that arise due to the complex and restrictive rules of hedge accounting. Ultimately, the severity of the accounting mismatch depends on whether the measurement approach used for the affected assets corresponds with the measurement of the financial liabilities.[17]

We examine whether recognized OCR gains and losses are reflected in stock-based measures and, in turn, whether OCR gains and losses yield useful information to investors. The relation between OCR gains and losses and stock-based measures is ex-ante unclear. If the information is not useful or if OCR estimates are too noisy, we expect coefficients for OCR gains and losses to be close to zero (i.e., insignificant).[18] If, however, investors interpret OCR gains and losses as a *normal* component of trading income, we expect OCR gains and losses to be positively associated with stock prices and stock returns. On the contrary, if OCR gains and losses reflect changes in the entity-wide credit risk (i.e., the asset-side effect of changes in credit risk dominates the liability-side effect), we expect OCR gains and losses to be negatively associated with stock prices and stock returns.

Regardless whether OCR gains and losses are positively or negatively associated with stock returns and stock prices, we expect volatility in OCR gains and losses to be positively associated with stock-based risk measures (i.e., risk relevant), as volatility in OCR gains and losses captures bank's exposure to credit risk. To the extent that we find OCR gains and losses to be risk relevant, this finding also supports the interpretation that OCR information is useful for investors.

[17] See IASB (2009) for a more detailed discussion about the controversies surrounding OCR.
[18] For example, Dong, Doukakis, and Ryan (2016) predict and find that banks measure their OCR adjustments with discretion.

2.3. Research Design

To examine investors' perception of OCR gains and losses, and in turn, whether such information is useful, we analyze the association between OCR gains and losses and capital-market outcomes. This approach assumes that capital markets are reasonably efficient, so that they can process financial statement information among other information into a single share price (Holthausen and Watts, 2001). Under this assumption, we should be able to detect whether OCR gains and losses are useful in equity valuation models.

Because there is no clear-cut choice for an empirical model, we use different research methodologies. We use return-relevance, value-relevance, and risk-relevance methodology to analyze whether OCR gains and losses are reflected in stock returns, in market value of equity, and in different stock-based risk measures, respectively. We use both return relevance and value relevance as both approaches have their advantages—return relevance is more subjective to measurement error (e.g., Bhat and Ryan 2015), whereas value relevance is more prone to omitted variable bias (e.g., Barth, Beaver, and Landsman, 2001 and Holthausen and Watts, 2001). Our risk-relevance tests complement the return- and value-relevance tests, providing more insights on whether OCR information is useful.

2.3.1. Return relevance

We start by examining the return relevance of OCR gains and losses. We closely follow Bhat and Ryan (2015), regressing share returns for the 12 months ending three months after the fiscal year end (*RET*) on net income (*NI*), other comprehensive income (*OCI*), and control variables.[19] We then disaggregate total net income into OCR gains and losses (*OCRGL*) and net income excluding OCR gains and losses (*NIBOCR*) (see Eq. (2.1)):

[19] In contrast to Bhat and Ryan (2015) we use share prices three months (rather than four months) after the reporting date because first quarter earnings announcements may already be available to investors in the fourth month. However, when we use share prices four months after the reporting date, the results do not change.

$$RET_{i,t} = \beta_0 + \beta_1 NIBOCR_{i,t} + \beta_2 OCRGL_{i,t} + \beta_3 OCI_{i,t} + \sum_{d=1}^{D} \gamma_d Controls_{d,i,t} + \varepsilon_{i,t}. \quad (2.1)$$

Subscript *i* and *t* denote a bank (*i*) in a given year (*t*) between 2006 and 2015. Because other comprehensive income (*OCI*) is unavailable in Datastream, we calculate other comprehensive income as comprehensive income minus net income.[20] We use control variables for differences in bank characteristics (*SIZE*, *LEV*, and *MTB*) and differences in the market risk across time (*VIX*). *SIZE* is the natural logarithm of total assets; *LEV* is total liabilities divided by total assets; *MTB* is market value of equity divided by the book value of equity; and *VIX* is the Chicago Board Options Exchange S&P 500 Volatility Index at each calendar year end.

We scale all regressor variables (right-hand-side variables) in Eq. (2.1) except the control variables by beginning-of-year market value of equity (three months after the fiscal year begins), and we express all amounts in U.S. Dollars. To mitigate the effects of outliers, we winsorize all variables at the 0.5% and 99.5% level, respectively (Bhat and Ryan, 2015). As we use panel data consisting of bank-year observations, we consistently use heteroscedasticity-robust standard errors clustered by bank throughout this paper (Froot, 1989 and Rogers, 1993). All our regressions include country-fixed and year-fixed effects to control for systematic differences across countries and years, respectively (Petersen, 2009).

2.3.2. Value relevance

Following prior related research (e.g., Barth and Clinch, 1998; Landsman, Peasnell, and Shakespeare 2008; and Fiechter and Novotny-Farkas, 2017), our second set of tests investigates the value relevance of reported balance sheet items and net income positions. More specifically, we regress market value of equity three month after the financial year end

[20] Comprehensive income is approximated by the change in equity from year t-1 to year t plus cash dividends paid in year t plus decreases in outstanding common and preferred stock in year t minus the amount received from the sale of common and preferred stock in year t.

(P) on assets, liabilities, and net income. To examine whether own credit risk is reflected in the market value of equity, we then disaggregate net income into OCR gains and losses (*OCRGL*) and net income excluding OCR gains and losses (*NIBOCR*) (see Eq. (2.2)):

$$P_{i,t} = \beta_0 + \beta_1 HFTA_{i,t} + \beta_2 FVOA_{i,t} + \beta_3 AFS_{i,t} + \beta_4 OA_{i,t} + \beta_5 HFTL_{i,t} + \beta_6 FVOL_{i,t} + \beta_7 OL_{i,t} + \beta_8 NIBOCR_{i,t} + \beta_9 OCRGL_{i,t} + \varepsilon_{i,t.} \tag{2.2}$$

We split assets and liabilities into different categories of financial instruments. *HFTA* (*HFTL*) are held-for-trading assets (liabilities) plus other derivative assets (liabilities). *FVOA* (*FVOL*) and *AFS* are fair-value-option assets (liabilities) and available-for-sale assets, respectively. *OA* (*OL*) are financial assets (liabilities) at amortized cost as well as non-financial assets (liabilities). We scale all variables by the number of common shares outstanding, and we express all amounts in U.S. Dollars.

Following Landsman, Peasnell, and Shakespeare (2008) we measure the market value of equity and the number of common shares outstanding three months after the financial year end. The regressor variables are all measured at the financial year end. Accordingly, we assume that investors process the information in the annual reports within three months after the financial year end. To avoid biased results due to extreme outliers, we follow Belsley, Kuh, and Welsch (1980) and Fox (1991), eliminating observations that have absolute value of studentized residuals greater than 2 (e.g., Song, Thomas, and Yi, 2010 and Fiechter and Novotny-Farkas, 2017).

2.3.3. Risk relevance

For the risk-relevance analysis, we closely follow Hodder, Hopkins, and Wahlen (2006), regressing stock-based risk measures (SMRs) on income-volatility measures. We use three

SMRs: total volatility in stock returns ($\sigma(RET)$), market model beta (*MM_Beta*), and the absolute values of long-term interest-rate betas (*LT_IR_Beta*) (see Eq. (2.3)).

$$SMR_{i,t} = \beta_0 + \beta_1 \sigma(NIBOCR)_{i,t} + \beta_2\, \sigma(OCRGL)_{i,t} + \beta_3\, \sigma(OCI)_{i,t} + \sum_{d=1}^{D} \gamma_d Controls_{d,i,t} + \varepsilon_{i,t}. \quad (2.3)$$

We adopt a five-year measurement period to allow income volatility and SMRs to vary over time, relaxing the restriction that risk is stationary for each bank over the 10 sample years. To proxy for total market-equity risk, we first compute for each bank the standard deviation of raw returns over each of the six 60-month periods ending with the last month of each year from 2010 to 2015. Second, we compute for each bank a market-model beta as a proxy for market-model risk (Hodder, Hopkins, and Wahlen, 2006). We estimate market-model betas by regressing bank stock returns on a market-wide index of value-weighted returns over each of the six 60-month periods ending with the last month of each year 2010–2015.[21] Third, we estimate interest-rate risk by regressing bank stock returns on monthly changes in long-term government bond yields over each of the six 60-month periods ending with the last month of each year from 2010 to 2015 (Flannery and James, 1984). If a bank has a net fixed-rate asset exposure (net fixed-rate liability exposure) to interest-rate changes, then the bank's share returns should be negatively (positively) associated with changes in interest rates, in turn leading to more negative (more positive) interest-rate betas. Hence we calculate the absolute value of the interest-rate beta to capture the exposure to interest-rate risk.

For our income volatility measures, we first separate comprehensive income into other comprehensive income, net income excluding OCR gains and losses, and OCR gains and losses. Second, we calculate the standard deviations of all three comprehensive income

[21] We use the MSCI value-weighted index for our analysis. However, repeating our analysis using the FTSE value-weighted index does not alter the results.

components over each of the six 60-month periods ending with the last month of each year from 2010 to 2015. As in the returns-relevance tests (see Eq. (2.1)), we use control variables for differences in bank characteristics (*SIZE*, *LEV*, and *MTB*) and differences in the market risk across time (*VIX*).

For this analysis, we scale all regressor variables except the control variables by beginning-of-year market value of equity and express all amounts in U.S. Dollars. To mitigate the effects of outliers, we winsorize all continuous model variables at the 0.5% and 99.5% levels of their distributions.

2.4. Sample Selection and Summary Statistics

2.4.1. Sample Selection Process

The sample selection process is outlined in Table 2.1. We begin our sample selection process by extracting all banks that are in the Bankscope database as of February 2016 (22,666). We restrict our sample to consolidated groups (-18,856) that comply with International Financial Reporting Standards (-2,945); are active at the time of the data collection (-39); are listed on a stock exchange (-308); and for which we find the ISIN code, the market value of equity, and the number of common shares outstanding in at least one year between 2006 and 2015 (-229). We complement our sample with consolidated bank groups that only appear on Datastream (+377). Again, we restrict the data in Datastream to groups that comply with International Financial Reporting Standards (-252) and for which we find the ISIN code, the market value of equity, and the number of common shares outstanding in at least one year between 2006 and 2015 (-46).[22]

[22] We use the term “banks” to denote bank holding companies.

This procedure yields 368 unique banks (3,680 bank-year observations from 2006 to 2015) before data collection on OCR gains and losses. We drop bank-year observations if financial statements are not publicly available (-758); if financial statements are not in English, German, or French (-178); if financial statements are (in fact) not in accordance with International Financial Reporting Standards (-257); if bank-years exhibit negative book value of equity (-8); and if we have missing data in the return-relevance models (i.e., *R*, *NI*, *OCI, SIZE*, *LEV*, *MTB*, *or VIX*) (-181). This procedure yields a base sample of 2,298 bank-year observations from 44 countries for the return-relevance tests. For our value-relevance models, we use a reduced sample of 2,243 observations, because we drop all observations with absolute values of studentized residuals larger than 2 (e.g. Belsley, Kuh, and Welsch, 1980 and Fox, 1991). For our risk-relevance models, we use rolling averages over six 60-month periods instead of annual data, resulting in a sample of 1,208 observations.

2.4.2. Descriptive Statistics

Table 2.2 shows summary statistics of all variables used in our main regressions. Return-relevance and value-relevance variables are measured at the year level, whereas risk-relevance variables are averaged over a 60-month period. The average bank is highly leveraged (mean value of 0.83 in the return-relevance model), which is a common feature for financial institutions. Consistent with prior literature, *HFTA* and *AFS* are the two major types of bank assets measured at fair value (e.g. Xie, 2016 and Fiechter and Novotny-Farkas, 2017). The amount of *HFTA* is relatively large because it combines held-for-trading assets with derivative assets held for trading and derivative assets held for hedging. We lose some observations in our risk-relevance models regarding the long-term interest-rate beta (*LT_IR_Beta*) due to missing country-level data.

Table 2.3, Panel A reports bank-years with non-zero OCR gains and losses by country in million U.S. Dollars (column A) and scaled with market value of equity (column B). Non-zero OCR gains and losses are concentrated within Europe with the exception of Australia, Canada, Republic of Korea, and South Africa. Panel A further reveals that most non-zero OCR observations are from Italy.[23] While mean and median OCR gains and losses scaled with market value of equity are close to zero, they can substantially differ within and across countries.

Table 2.3, Panel B reports OCR gains and losses by sample year. OCR gains spiked during the financial crisis in 2008 and the European sovereign debt crisis in 2011. Both years are followed by an inverse OCR trend, leading to large OCR losses in 2009 and 2012. Periodical OCR gains and losses range from -7.517bn (Min.) in 2012 to 6.57bn in 2008 (Max.).

2.5. Empirical Results

2.5.1. Return Relevance

Table 2.4 reports regression results of Eq. (2.1). To link prior research and to establish a benchmark for our main results, column (1) provides regression results of *RET* on *NI, OCI,* country-fixed and year-fixed effects. Column (2) introduces our variable of interest, *OCRGL,* into the benchmark model. In column (3), we complement our main regression with control variables that should capture differences in bank characteristics (*SIZE*, *LEV*, and *MTB*) and differences in the market risk across years (*VIX*). To benchmark OCR gains and losses against another income component, we separate in column (4) interest income (*INTEREST*) from *NIBOCR*. Because interests are an important and stable source of income for banks, we

[23] Note that Italian banks prepare highly standardized financial statement notes including a standardized table "financial liabilities designated at fair value: breakdown", which includes information on own credit risk. This might foster clear disclosure of OCR results.

predict that markets perceive interests as a "normal" income component, and thus we predict a positive correlation between *INTEREST* and *R*. In column (5), we use a subsample of banks with non-zero FVOL, thereby mitigating concerns that the coefficient estimates for *OCRGL* are mainly driven by banks that do not apply the fair value option on liabilities.

In the benchmark model reported in column (1), the R^2 of 41.3% is close to that in Bhat and Ryan (2015) of 41.8%. The high R^2 is largely due to substantial banking-wide performance variation across years, which is captured by the year-fixed effects. The coefficients for *NI* and *OCI* of 0.059 and 0.043, respectively, are significantly positive at the 1% level, but substantially lower than one, suggesting considerable noise in these variables.[24]

In column (2), the coefficient for the test variable *OCRGL* of -2.725 is significantly negative at the 1% level, suggesting that investors perceive OCR gains (losses) as a negative (positive) signal for banks' economic performance. This result is consistent with the notion that investors do not perceive OCR gains and losses as a "normal" component of income. Rather, OCR gains and losses reflect changes in the entity-wide credit risk (i.e., the asset-side effect dominates the liability-side effect). The magnitude of the coefficient suggests that the effect is substantial and that overall changes in an entity's credit risk is a crucial component of bank's economic performance.

Including the control variables in column (3) does not alter our findings. In addition, all control variables have the expected sign. The positive and significant coefficient for *INTEREST* in column (4) is consistent with investors perceiving interests as a normal income component—in contrast to the OCR gains and losses—which increases confidence in our inferences. The analysis in column (5) shows that the coefficient for *OCRGL* remains very

[24] Winsorizing the two variables at the 5% (10%) [25%] level rather than at the 0.5% level shows that the magnitude of the variables *NI* and *OCI* increases to 0.979 (1.743) [3.486] and 0.186 (0.209) [0.548], respectively. All variables remain significantly positive at the 1% level. This result indicates that *NI* is a permanent component for non-extreme observations whereas *OCI* remains a transitory component across all levels. However, winsorizing at these higher levels substantially reduces the variation of *OCRGL* to an extent at which we no longer can draw meaningful inferences about the market perception of OCR gains and losses.

similar for the subsample of bank-years with non-zero FVOL. Hence the inclusion of bank-years that do not use the fair value option seem not to drive our results. Across all model specifications in column (2) to (5), the coefficients on *OCRGL* remain in a range between -2 and -3 and significant at the 1% level.

2.5.2. Value Relevance

Table 2.5 reports estimation of Eq. (2.2) in column (2). We use the value-relevance model to test whether and how OCR gains and losses are reflected in stock prices. Again, to link prior research and to establish a benchmark for our main results, we regress stock prices on reported balance sheet values in column (1). The coefficient estimates all have the expected sign, i.e., positive for asset positions and net income and negative for liability positions. All asset fair value positions (*HFTA*, *FVOA*, and *AFS*) are not significantly different from the theoretical value of 1 (untabulated F-stat = 0.33, 0.06, and 0.52, respectively) and all liability fair value positions (untabulated *HFTL* and *FVOL*) are not significantly different from the theoretical value of -1 (F-stat = 0.06 and 0.16, respectively). Overall, the estimation coefficients are close to those in Fiechter and Novotny-Farkas (2017) except for the coefficient estimates for *FVOA* (1.064 compared to 0.709).[25]

In column (2), we distinguish between OCR gains and losses (*OCRGL*) and net income excluding OCR gains and losses (*NIBOCR*). Regression results show that both *NIBOCR* and *OCRGL* are significantly different from zero (t-stats = 2.15 and -2.19, respectively). The negative coefficient of -8.599 for *OCRGL* is in line with our return-relevance findings, suggesting that OCR gains (losses) is a negative (positive) sign for the economic performance. We interpret this finding as evidence that OCR gains and losses reflect changes

[25] The difference between our findings and the findings in Fiechter and Novotny-Farkas (2017) related to *FVOA* are likely because of different sample periods: we use a sample period from 2006 to 2015, whereas Fiechter and Novotny-Farkas (2017) use a shorter period (2006–2009). In addition, Fiechter and Novotny-Farkas (2017) argue that fair value experience improves the value relevance of FVO assets, which is consistent with our finding.

in the entity-wide credit risk, i.e., the asset-side effect of changes in credit risk dominates the liability-side effect.

2.5.3. Risk Relevance

Table 2.6 reports estimation of Eq. (2.3), testing the association between stock-based risk measures and the variation in OCR gains and losses. First, we separately regress return volatility (*σ(RET)*) on volatility of net income excluding the effect of own credit risk (*σ(NIBOCR)*) in column (1), on volatility of OCI (*σ(OCI)*) in column (2), and on volatility of OCR gains and losses (*σ(OCRGL)*) in column (3), respectively. In all specifications, we include control variables that should capture differences in bank characteristics (*SIZE*, *LEV*, and *MTB*) and differences in the market risk across years (*VIX*).

Column (4) combines the three explanatory variables from the first three columns. Regression results show a positive relation between stock-return volatility and volatility of OCR gains and losses (*σ(OCRGL)*), significant at the 5% level. In column (3), the magnitude of the coefficient for the test variable (*σ(OCRGL))* of 0.222 is larger than the coefficient for *σ(NIBOCR)* in column (1). In column (4), we find that *σ(OCRGL)* remains significant (t-stats = 2.01) and relatively stable across columns (3) and (4): 0.222 and 0.229, respectively. This finding suggests that OCR gains and losses are risk relevant.

We repeat the regression in column (5) by using *MM_Beta* as our dependent variable. Similar to Hodder, Hopkins, and Wahlen (2006), our results do not support reliable inference that any of the three comprehensive-income-volatility measures are associated with

MM_Beta. In column (6), we use *LT_IR_Beta* as dependent variable. The regression coefficient for *σ(OCRGL)* of 0.810 is only marginally significant (t-stat = 1.57).[26]

2.6. Additional Analysis

2.6.1. Institutional Differences in OCR Information Processing

Prior experimental literature argues that financial statement users are likely to misinterpret OCR gains (losses) as a signal that an entity's credit risk is improving (deteriorating) (Gaynor, McDaniel, and Yohn, 2011; Lachmann, Wöhrmann, and Wömpener, 2011; and Lachmann, Stefani, and Wöhrmann, 2015). In addition, Gaynor, McDaniel, and Yohn (2011) find that enhanced disclosure improves processing of OCR information. Therefore, we test whether the association between OCR gains and losses and our stock-based measures varies with different institutional factors, such as investor sophistication or the information environment. We create three indicator variables that proxy for different institutional factors: First, we create a variable *HIGH_ANACOV* equal to 1 if an entity with non-zero OCR gains and losses has above median analyst coverage, and 0 otherwise. Second, we follow Beck and Levine (2002) and Fiechter and Novotny-Farkas (2017) and create a variable *MARKET_BASED* equal to 1 if an entity operates in a market-based economy, and 0 if it operates in a bank-based economy. Third, we create a variable *IO* equal to 1 if an entity with non-zero OCR gains and losses has above median percentage of institutional investors, and 0 otherwise. We then interact all three variables with our main variable *OCRGL*.

[26] In contrast to Hodder, Hopkins, and Wahlen (2006), our regression includes control variables for *SIZE*, *LEV*, *MTB*, and *VIX*; country-fixed effects; year-fixed effects; and standard errors clustered by firms. However, we do not control for total exposure arising from derivatives held (*EXP*) and absolute value of the excess of fixed-rate assets over fixed-rate liabilities subject to repricing within one year (*GAP*) due to missing data availability. Removing our control variables from the model results in a significant *σ(OCRGL)* of 0.978 (t-stat = 1.95). Removing the fixed-effects increases the significance of *σ(OCRGL)* even further (t-stat = 3.09), which is more consistent with the findings of Hodder, Hopkins, and Wahlen (2006).

Table 2.7 shows the baseline return-relevance result in column (1) and all three extensions with the three institutional variables. We find that all interaction terms (*OCRGL**institutional factors) are not statistically significant from zero and that the main variable *OCRGL* remains significantly negative. This finding suggests that different levels of investor sophistication and/or different information environments do not alter the information processing of OCR gains and losses. These results mitigate concerns that investors systematically misinterpret OCR gains and losses. Untabulated findings also reveal that investor sophistication does neither affect the value-relevance nor the risk-relevance results.

2.6.2. Asset Write-Downs due to Changes in Credit Risk

To bolster our interpretation that OCR gains and losses are linked to and dominated by credit risk changes on the asset-side, we compare OCR gains and losses with asset-write downs induced by changes in credit risk. We use loan losses (WC01273) and changes in loan loss provisions (WC01271) as proxies for credit-related asset write-downs.[27] To investigate whether asset-side losses (gains) are linked with liability-side gains (losses), we first investigate correlations between OCR gains and losses and credit-related asset write-downs. Second, to test whether asset-side losses (gains) dominate liability-side gains (losses), we compare the magnitude of OCR gains and losses with that of credit-related asset write-downs.

We find that OCR gains and losses are positively correlated with loan losses (0.110) and changes in loan loss provisions (0.188), respectively, with correlation coefficients being significant at the 1% level. This result indicates that banks reporting OCR gains also increase their loan loss provisions and report higher loan losses. In addition, net income excluding OCR gains and losses is significantly and negatively correlated with OCR gains and losses (-0.127), loan losses (-0.165), and changes in loan loss provisions (-0.104), respectively. This

[27] We retrieve loan losses and changes in loan loss provisions from Datastream. Due to missing values, our sample is reduced to 918 observations. We scale all variables by beginning-of-year market value of equity.

result suggests that OCR gains (losses) are associated with weaker (better) economic performance.

Second, untabulated summary statistics reveal that mean (median) loan losses of 5.52% (2.24%) and changes in loan loss provisions of 1.66% (0.14%) dominate OCR gains and losses of 0.12% (0.00%). In addition, the upper (lower) 5 percentile reveals that large OCR gains (losses) of 0.97% (-0.62%) are dominated by even larger changes in loan loss provisions of 12.93% (-7.65%) and loan losses of 22.81% (0.05%), respectively.[28]

Overall, these additional analyses support our inferences that OCR gains and losses on the liability-side are linked to and dominated by changes on the asset-side. This finding further suggests that OCR gains and losses should not be interpreted in "isolation". Interpreting OCR gains and losses on the liability side together with credit-related changes on the asset side is no longer "counterintuitive", but rather reflects entity-wide changes in credit risk.

2.6.3. Leverage

Barth, Hodder, and Stubben (2008) find that 27 percent of the downgraded firms recognize asset write downs that are smaller than unrecognized gains from decreases in debt value. We presume that such a result is most likely to occur for highly leveraged banks. Hence we investigate whether the association between OCR gains and losses and stock returns varies with leverage. We create three indicator variables for different percentiles of leverage (i.e., p25, p50, and p75). We then interact all three indicator variables with our main variable *OCRGL*.

While none of the untabulated interaction terms is significantly different from zero, the coefficients for *OCRGL* remain significantly negative at the 1% level. This finding does not

[28] Note that loan losses, by definition, cannot be negative. Therefore, the minimum for loan losses is 0.00%.

suggest that the negative association between OCR gains and losses and stock returns becomes positive at different levels of leverage. We, however, note that the median leverage of our sample bank is relatively high (0.91) and even higher for the subsample of banks with non-zero OCR gains and losses (0.94). Therefore, our findings might not be generalizable to non-financial firms.

2.7. Conclusion

Against the backdrop of the intense debate on whether and how OCR gains and losses should be reflected in the value of FVOL, a better understanding of the usefulness of OCR gains and losses is important for several reasons: First, understanding the relation between OCR gains and losses and stock-based measures can help guide future standard setting. Second, as banks have high leverage compared to non-financial firms, small fluctuations in the amount of liabilities may strongly impact comprehensive income and book value of equity. Third, banks are highly exposed to credit risk due to their business model. Counterparty credit risk translates, amongst other factors, directly into bank's own credit risk. Hence the assessment of entity's risk exposure is crucial to understand asset, liability, and earnings fluctuations rooted in credit risk fluctuations.

Using a global sample of IFRS banks, we investigate whether OCR gains and losses are reflected in stock-based measures such as stock prices, stock returns, and stock-based risk measures from 2006 to 2015. We find that OCR gains and losses are negatively associated with stock returns and stock prices, respectively, indicating that the market perceives OCR gains (losses) as a negative (positive) signal for the bank's (future) economic performance. In addition, we find that the volatility in OCR gains and losses is positively associated with stock-based risk measures, i.e., OCR gains and losses are risk relevant. These results are in line with the notion that OCR gains and losses reflect the entity-wide change in credit risk, i.e., the asset-side effect of changes in credit risk dominates the liability-side effect.

We acknowledge that our results should be interpreted with some caveats in mind. First, because we focus on banks, which are highly exposed to credit risk, results may not be generalizable to non-financial institutions. Second, the low frequency with which banks choose the fair value option for financial liabilities and the even lower frequency of banks that disclose OCR gains and losses may also limit the results' generalizability.

Despite these limitations, this study makes several contributions to the literature. First, we show that OCR gains and losses are reflected in stock-based measures. Second, we provide empirical evidence that OCR gains and losses are *not* counterintuitive when considered together with asset-side changes in credit risk. Third, we mitigate concerns that investors systematically misinterpret OCR gains and losses when assessing an entities economic performance.

References

Bank for International Settlements (BIS). 2009. *Basel III: A global regulatory framework for more resilient banks and banking systems*. Retrieved from: http://www.bis.org/publ/bcbs189.pdf.

Barth, M.E., Beaver, W.H., and Landsman, W.R. 2001. The relevance of the value relevance literature for financial accounting standard setting: another view. *Journal of Accounting and Economics* (31): 77–104.

Barth, M.E. and Clinch, G. 1998. Revalued financial, tangible, and intangible assets: Associations with share prices and non-market-based value estimates. *Journal of Accounting Research* (36): 199–233.

Barth, M.E., Hodder, L.D., and Stubben, S.R. 2008. Fair value accounting for liabilities and own credit risk. *The Accounting Review* (83): 629–664.

Beck, T. and Levine, R. 2002. Industry growth and capital allocation: Does having a market- or bank-based system matter? *Journal of Financial Economics* (64): 147–180.

Belsley, D.A., Kuh, E., and Welsch, R.E. 1980. *Regression diagnostics: Identifying influential data and sources of collinearity*. New York: John Wiley & Sons.

Bhat, G. and Ryan, S.G. 2015. The impact of risk modeling on the market perception of banks' estimated fair value gains and losses for financial instruments. *Accounting, Organizations and Society* (46): 81–95.

Cedergren, M.C., Chen, C., and Chen, K. 2015. The implication of unrecognized intangible assets on the relation between market valuation and debt valuation adjustment. Paper presented at the 2014 Canadian Academic Accounting Association Annual Conference.

CFA Institute. 2009. Comment Letter (CL107) on the Discussion Paper on Credit Risk in Liability Measurement. Retrieved from http://www.ifrs.org/Current-Projects/IASB-Projects/Credit-Risk-in-Liability-Measurement/DP-Jun-09/Comment-Letters/Pages/Comment-letters.aspx.

Cooper, S. 2015. Other comprehensive income relevance: IASB's Cooper explains. Video Interview. Retrieved from https://www.cfainstitute.org/learning/products/multimedia/Pages/119944.aspx.

Dong, M., Doukakis, L., and Ryan, S.G. 2016. Banks' discretion over the debt valuation adjustment for own credit risk. *Working Paper*.

Ederington, L. and Yawitz, J. 1987. The bond rating process, in Altman, E. ed.: *Handbook of Financial Markets and Institutions*, 6th ed. New York: John Wiley and Sons.

Essen, Y. 2009. Lloyd's to buy back £100m of its debt. *The Telegraph*. Retrieved from http://www.telegraph.co.uk/finance/newsbysector/banksandfinance/insurance/5199813/Lloyds-to-buy-back-100m-of-its-debt.html.

Fiechter, P. and Novotny-Farkas, Z. 2017. The impact of the institutional environment on the value relevance of fair values. *Review of Accounting Studies* (22): 392–429.

Flannery, M. and James, C. 1984. The effect of interest rate changes on the common stock returns of financial institutions. *Journal of Finance* (39): 1141–1153.

Fox, J. 1991. *Regression diagnostics*. Newbury Park, CA: Sage.

Froot, K. A. 1989. Consistent covariance matrix estimation with cross-sectional dependence and heteroskedasticity in financial data. *Journal of Financial and Quantitative Analysis* (24): 333–355.

Gaynor, L.M., McDaniel, L., and Yohn, T.L. 2011. Fair value accounting for liabilities: The role of disclosure in unraveling the counterintuitive income statement effect from credit risk changes. *Accounting, Organizations and Society* (36): 125–134.

Goh, J.C. and Ederington, L.H. 1993. Is a bond rating downgrade bad news, good news, or no news for stockholders. *The Journal of Finance* (48): 2001–2008.

Griffin, P.A. and Sanvicente, A.Z. 1982. Common stock returns and rating changes: A methodological comparison. *The Journal of Finance* (37): 103–119.

Guider, I. 2009. Bank of Ireland to buy back debt after profit slumps. *Independent.ie*. Retrieved from http://www.independent.ie/business/irish/bank-of-ireland-to-buy-back-debt-after-profit-slumps-26537225.html.

Hand, J., Holthausen, R., and Leftwich, R. 1992. The effect of bond rating agency announcements on bond and stock prices. *Journal of Finance* (47): 733–752.

Hodder, L.D., Hopkins, P.E., and Wahlen, J.M. 2006. Risk-relevance of fair value income measures for commercial banks. *The Accounting Review* (81): 337–375.

Holthausen, R.W. and Leftwich, R.W. 1986. The effect of bond rating changes on common stock prices. *Journal of Financial Economics* (17): 57–89.

Holthausen, R.W. and Watts, R.L. 2001. The relevance of the value-relevance literature for financial accounting standard setting. *Journal of Accounting and Economics* (31): 3–75.

HSBC. 2009. Comment Letter (CL101) on the Discussion Paper on Credit Risk in Liability Measurement. Retrieved from http://www.ifrs.org/Current-Projects/IASB-Projects/Credit-Risk-in-Liability-Measurement/DP-Jun-09/Comment-Letters/Pages/Comment-letters.aspx.

International Accounting Standards Board (IASB). 2009. *Staff paper accompanying discussion paper: Credit risk in liability measurement*. Retrieved from http://www.ifrs.org/

Current-Projects/IASB-Projects/Credit-Risk-in-Liability-Measurement/DP-Jun-09/Documents/CreditRiskLiabilitStaff.pdf.

International Accounting Standards Board (IASB). 2013. Financial Instruments: Recognition and Measurement. International Accounting Standard 39. *International Financial Reporting Standards*. London, U.K.: IASB.

International Accounting Standards Board (IASB). 2014a. Financial Instruments: Disclosures. International Financial Reporting Standard 7. *International Financial Reporting Standards*. London, U.K.: IASB.

International Accounting Standards Board (IASB). 2014b. Financial Instruments. International Financial Reporting Standard 9. *International Financial Reporting Standards*. London, U.K.: IASB.

International Accounting Standards Board (IASB). 2014c. *Project summary: IFRS 9 – Financial instruments*. Retrieved from http://www.ifrs.org/Current-Projects/IASB-Projects/Financial-Instruments-A-Replacement-of-IAS-39-Financial-Instruments-Recognitio/Documents/IFRS-9-Project-Summary-July-2014.pdf.

JP Morgan Chase. 2009. Comment Letter (CL99) on the Discussion Paper on Credit Risk in Liability Measurement. Retrieved from http://www.ifrs.org/Current-Projects/IASB-Projects/Credit-Risk-in-Liability-Measurement/DP-Jun-09/Comment-Letters/Pages/Comment-letters.aspx.

Kliger, D. and Sarig, O. 2000. The information value of bond rating. *The Journal of Finance* (55): 2879–2902.

KPMG. 2009. Comment Letter (CL51) on the Discussion Paper on Credit Risk in Liability Measurement. Retrieved from http://www.ifrs.org/Current-Projects/IASB-Projects/Credit-Risk-in-Liability-Measurement/DP-Jun-09/Comment-Letters/Pages/Comment-letters.aspx.

Lachmann, M., Stefani, U., and Wöhrmann, A. 2015. Fair value accounting for liabilities: Presentation format of credit risk changes and individual information processing. *Accounting, Organizations and Society* (41): 21–38.

Lachmann, M., Wöhrmann, A., and Wömpener, A. 2011. Acquisition and integration of fair value information on liabilities into investors' judgement. *Review of Accounting and Finance* (10): 385–410.

Landsman, W.R., Peasnell, K.V., and Shakespeare, C. 2008. Are asset securitizations sales or loans? *Accounting Review* (83): 1251–1272.

Lipe, R.C. 2002. Fair valuing debt turns deteriorating credit quality into positive signals for Boston Chicken. *Accounting Horizons* (16): 169–181.

Merton, R.C. 1974. On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance* (29): 449–470.

Petersen, M.A. 2009. Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies* (22): 435–480.

Rapoport, M. 2015. Banks get relief on accounting headache: New treatment to alter lenders' debt-value adjustments. *The Wall Street Journal*. Retrieved from http://www.wsj.com/ articles/ rule-on-valuation-of-banks-liabilities-to-be-scrapped-1452013335.

Rogers, W. H. 1993. Regression standard errors in clustered samples. *Stata Technical Bulletin* (13): 19–23.

Song, C.J., Thomas, W.B., and Yi, H. 2010. Value relevance of FAS no. 157 fair value hierarchy information and the impact of corporate governance mechanisms. *The Accounting Review* (85): 1375–1410.

Steiner, R. 2009. Cut-price debt deal for Canary Wharf developer. *MailOnline*. Retrieved from http://www.dailymail.co.uk/money/article-1168847/Cut-price-debt-deal-Canary-Wharf-developer.html.

Strong, J.S. 1990. Valuation effects of holding gains in long-term debt. *Journal of Accounting and Economics* (13): 267–283.

Wansley, J.W. and Clauretie, T.M. 1985. The impact of creditwatch placement on equity returns and bond prices. *Journal of Financial Research* (8): 31–42.

UBS. 2009. Comment Letter (CL74) on the Discussion Paper on Credit Risk in Liability Measurement. Retrieved from http://www.ifrs.org/Current-Projects/IASB-Projects/Credit-Risk-in-Liability-Measurement/DP-Jun-09/Comment-Letters/Pages/Comment-letters.aspx.

Xie, B. 2016. Does fair value accounting exacerbate the procyclicality of bank lending? *Journal of Accounting Research* (54): 235–274.

Tables

Table 2.1: Sample Selection Process

	Change	Remaining
All banks in Bankscope		22,666
Ultimate owners only	-18,856	3,810
Accounting standard: IFRS and IAS	-2,945	865
Active banks only	-39	826
Listed banks only	-308	518
ISIN, MV and CSO available from 2006 to 2015	-229	289
Additional active listed banks in Datastream	+377	666
Accounting standard: IFRS and IAS	-252	414
ISIN, MV and CSO available from 2006 to 2015	-46	368
Banks before OCR data collection		**368**
Start (Firm-year observations)		3,680
Financial statements publicly available	-758	2,922
Financial statements not in English, German, or French	-178	2,744
Financial statement not in accordance with IFRS or equivalent	-257	2,487
Negative equity	-8	2,479
Missing data in the return-relevance models	-181	2,298
Base sample		2,298
Sample for return relevance (winsorized at 0.5% and 99.5%)	0	**2,298**
Sample for value relevance (elimination of absolute value of studentized residuals >2)	-55	**2,243**
Sample for risk relevance (winsorized at 0.5% and 99.5%; rolling averages over 60-months)	-1,090	**1,208**

This table presents the sample selection process. We begin our sample selection process by extracting all banks that are in the Bankscope database as of February 2016 (22,666). We restrict our sample to consolidated groups (-18,856) that comply with International Financial Reporting Standards (-2,945); are active at the time of the data collection (-39); are listed on a stock exchange (-308); and for which we find the ISIN code, the market value of equity, and the number of common shares outstanding in at least one year between 2006 and 2015 (-229). We complement our sample with consolidated bank groups that only appear on Datastream (+377). Again, we restrict the data in Datastream to groups that comply with International Financial Reporting Standards (-252) and for which we find the ISIN code, the market value of equity, and the number of common shares outstanding in at least one year between 2006 and 2015 (-46). This procedure yields 368 unique banks.

For each bank we gather data from 2006 until 2015 leading to 3,680 bank-year observations. We lose some bank-year observations if financial statements are not publicly available (-758); if financial statements are not in English, German, or French (-178); if financial statements are (in fact) not in accordance with IFRS or equivalent accounting standards (-257); if bank-years exhibit negative book value of equity (-8); and if we have missing data in the return-relevance models (-181). Eventually, this procedure yields a base sample of 2,298 bank-year observations. For our value relevance models, we use a reduced sample of 2,243 observations, because we drop all observations with absolute values of studentized residuals larger than 2. For our risk relevance models, we use rolling averages over six 60-month periods instead of annual data, resulting in a sample of 1,208 observations.

Table 2.2: Descriptive Statistics

Variable	N	Mean	Std. dev.	Min	p25	Median	p75	Max
Return relevance								
RET	2298	0.05	0.51	-0.99	-0.22	-0.02	0.22	3.96
NI	2298	0.15	1.09	-3.60	0.05	0.09	0.13	15.12
NIBOCR	2298	0.15	1.10	-3.60	0.05	0.09	0.13	15.12
NIBOCRBINT	2298	-0.71	2.43	-27.93	-0.69	-0.27	-0.04	8.05
INTEREST	2298	0.77	2.12	0.00	0.06	0.33	0.74	27.53
OCRGL	2298	0.00	0.01	-0.11	0.00	0.00	0.00	0.05
OCI	2298	-0.13	1.54	-20.49	-0.07	0.00	0.05	1.56
SIZE	2298	9.94	2.45	4.07	8.20	9.85	11.56	15.05
LEV	2298	0.83	0.21	0.02	0.84	0.91	0.94	0.99
MTB	2298	1.38	1.33	0.00	0.61	1.02	1.67	9.27
VIX	2298	20.38	6.89	11.56	17.75	18.21	22.50	40.00
Value relevance								
P	2243	25.03	151.60	0.03	2.37	7.36	21.08	5,949.35
HFTA	2243	38.38	165.99	0.00	0.05	1.10	14.02	3,193.49
FVOA	2243	28.54	388.40	0.00	0.00	0.00	3.30	12,218.22
AFS	2243	37.94	579.94	0.00	0.16	2.20	15.33	27,069.75
OA	2243	349.83	3,314.25	0.04	9.70	51.52	171.33	145,241.90
HFTL	2243	26.06	125.63	0.00	0.00	0.34	7.09	2,958.37
FVOL	2243	42.03	753.80	0.00	0.00	0.00	0.85	28,816.35
OL	2243	356.31	3,027.31	0.00	8.77	53.36	188.36	131,077.80
NI	2243	2.86	46.60	-165.02	0.10	0.54	1.74	2,147.08
NIBOCR	2243	2.85	46.59	-165.02	0.10	0.54	1.73	2,147.08
OCR	2243	0.01	0.68	-3.73	0.00	0.00	0.00	30.11
Risk relevance								
σ(R)	1208	0.12	0.05	0.03	0.08	0.11	0.14	0.39
MM_Beta	1208	0.99	0.48	0.00	0.65	0.92	1.29	2.99
LT_IR_Beta	1070	0.42	0.32	0.00	0.16	0.37	0.62	1.40
σ(NI)	1208	0.38	2.47	0.00	0.02	0.04	0.12	29.31
σ(NIBOCR)	1208	0.29	1.62	0.00	0.03	0.06	0.14	18.00
σ(OCRGL)	1208	0.01	0.02	0.00	0.00	0.00	0.00	0.14
σ(OCI)	1208	0.41	2.17	0.00	0.05	0.09	0.18	25.09
SIZE	1208	9.79	2.44	3.96	7.98	9.71	11.36	14.68
LEV	1208	0.66	0.16	0.03	0.67	0.73	0.75	0.78
MTB	1208	1.07	0.95	0.00	0.50	0.82	1.30	7.24
VIX	1208	22.16	3.12	17.70	19.00	22.85	25.52	25.85

Table 2.3: Non-Zero OCR Gains and Losses by Country and Year

Panel A: OCR gains and losses by country

	OCR gains and losses (column A)								OCR gains and losses scaled by market value of equity (column B)							
Country	**N**	**Mean**	**Std. dev.**	**Min**	**p25**	**Median**	**p75**	**Max**	**N**	**Mean**	**Std. dev.**	**Min**	**p25**	**Median**	**p75**	**Max**
Australia	30	-3.27	83.89	-204.75	-36.52	-0.27	41.14	154.61	30	0.000	0.002	-0.004	-0.001	0.000	0.001	0.007
Austria	14	26.60	128.97	-190.70	-3.75	4.45	61.92	322.58	14	0.004	0.021	-0.029	-0.001	0.000	0.005	0.049
Belgium	7	-34.51	461.31	-934.74	-85.43	18.47	71.10	628.30	7	0.001	0.040	-0.069	-0.003	0.001	0.005	0.070
Canada	18	14.78	94.20	-68.30	-21.10	0.39	5.03	366.87	18	0.000	0.001	-0.001	0.000	0.000	0.000	0.005
Denmark	8	106.90	1,088.09	-1,156.91	-811.17	80.72	709.37	2,054.29	8	0.036	0.133	-0.067	-0.038	0.002	0.040	0.349
France	26	-59.82	953.59	-2,196.44	-464.07	77.81	519.38	1,544.79	26	0.006	0.046	-0.064	-0.012	0.002	0.026	0.187
Germany	19	136.71	1,427.70	-3,591.16	-84.73	26.32	280.82	4,688.63	19	0.008	0.050	-0.075	-0.004	0.001	0.012	0.184
Greece	13	18.30	183.54	-325.19	-20.68	-4.73	21.73	382.21	13	-0.027	0.122	-0.403	-0.022	-0.002	0.008	0.101
Ireland	9	8.76	236.21	-391.56	-12.10	11.95	72.70	482.96	9	0.029	0.102	-0.066	-0.004	0.001	0.015	0.292
Italy	75	9.68	174.38	-626.29	-9.60	-0.32	26.87	602.58	75	0.006	0.063	-0.281	-0.003	0.000	0.006	0.355
Korea, Rep.	12	1.40	5.52	-8.19	-0.52	-0.10	4.12	13.31	12	-0.001	0.005	-0.015	-0.001	0.000	0.000	0.001
Netherlands	20	0.25	242.89	-489.40	-33.40	-1.05	2.09	834.54	20	0.000	0.012	-0.020	-0.004	-0.001	0.002	0.031
Norway	15	11.29	47.14	-47.60	-1.28	2.58	7.23	171.83	15	0.024	0.321	-0.689	-0.007	0.000	0.030	0.986
Portugal	17	8.46	88.28	-152.21	-32.75	-4.85	66.08	167.33	17	0.005	0.024	-0.032	-0.011	-0.001	0.023	0.056
South Africa	23	1.81	14.71	-37.32	-2.41	1.53	8.16	48.82	23	0.000	0.002	-0.009	0.000	0.000	0.001	0.005
Sweden	22	6.14	259.46	-874.69	-12.05	0.37	9.61	734.59	22	0.000	0.006	-0.020	-0.001	0.000	0.000	0.018
Switzerland	18	-16.75	1,006.92	-2,405.64	-162.03	-6.96	293.87	1,909.15	18	0.006	0.056	-0.084	-0.009	-0.003	0.010	0.167
United Kingdom	49	-100.24	2,449.31	-7,516.57	-88.37	15.93	457.91	6,570.00	49	-0.001	0.056	-0.294	-0.006	0.000	0.008	0.134
Total	395	-3.70	984.16	-7,516.57	-23.05	0.06	63.13	6,570.00	395	0.004	0.079	-0.689	-0.003	0.000	0.005	0.986

Panel B:OCR gains and losses by year

	OCR gains and losses (column A)								OCR gains and losses scaled by market value of equity (column B)							
Country	**N**	**Mean**	**Std. dev.**	**Min**	**p25**	**Median**	**p75**	**Max**	**N**	**Mean**	**Std. dev.**	**Min**	**p25**	**Median**	**p75**	**Max**
2006	10	-44.00	121.39	-388.00	-14.51	-3.19	-1.28	6.32	10	-0.002	0.005	-0.016	-0.002	0.000	0.000	0.001
2007	24	229.67	431.78	-29.24	-0.63	16.08	290.73	1,619.00	24	0.005	0.009	-0.002	0.000	0.002	0.007	0.035
2008	33	628.59	1,464.90	-471.54	-1.25	84.97	299.83	6,570.00	33	0.072	0.183	-0.032	0.000	0.007	0.067	0.986
2009	38	-463.62	1,316.03	-6,533.00	-204.75	-9.69	11.91	734.59	38	-0.030	0.114	-0.689	-0.022	-0.001	0.001	0.046
2010	41	39.60	295.96	-874.69	-0.32	8.16	119.40	720.09	41	0.015	0.049	-0.020	0.000	0.001	0.011	0.292
2011	42	475.14	990.98	-489.40	3.67	69.39	380.36	4,186.77	42	0.026	0.093	-0.403	0.000	0.011	0.047	0.355
2012	47	-645.00	1,719.82	-7,516.57	-437.71	-20.01	-0.29	834.54	47	-0.031	0.064	-0.294	-0.047	-0.005	0.000	0.047
2013	53	-127.62	369.71	-2,196.44	-101.00	-3.49	1.92	177.76	53	-0.004	0.011	-0.045	-0.006	-0.001	0.000	0.038
2014	52	-1.59	163.11	-406.26	-33.50	-3.09	2.05	753.86	52	-0.002	0.010	-0.034	-0.004	-0.001	0.000	0.049
2015	55	107.67	238.43	-177.07	-1.60	7.23	108.63	1,002.00	55	0.004	0.010	-0.015	0.000	0.001	0.007	0.040
Total	395	-3.70	984.16	-7,516.57	-23.05	0.06	63.13	6,570.00	395	0.004	0.079	-0.689	-0.003	0.000	0.005	0.986

This table reports descriptive statistics of absolute OCR gains and losses (column A) and OCR gains and losses scaled by market value of equity (column B) for bank-years with non-zero OCR gains and losses by countries (Panel A) and by years (Panel B). OCR gains and losses are expressed in million U.S. Dollars.

Table 2.4: Return Relevance of OCR Gains and Losses

Dependent variable:		*RET*	*RET*	*RET*	*RET*	*RET*
Variables		(1)	(2)	(3)	(4)	(5)
	Predicted sign	Base sample	Base sample	Base sample	Base sample	FVOL users only
NI	+	0.059 *** (2.76)				
NIBOCR	+		0.058 *** (2.79)	0.058 *** (2.89)		0.009 (0.21)
NIBOCRBINT	+				0.025 *** (4.08)	
INTEREST	+				0.013 *** (2.91)	
OCRGL	**?**		**-2.725 ***** **(-3.91)**	**-2.787 ***** **(-4.07)**	**-2.827 ***** **(-4.28)**	**-2.243 ***** **(-3.28)**
OCI	+	0.043 *** (3.19)	0.043 *** (3.25)	0.040 *** (3.14)	0.013 *** (2.80)	0.005 (0.15)
SIZE	?			0.004 (0.86)	0.004 (0.91)	-0.008 (-0.95)
LEV	-			-0.169 *** (-3.64)	-0.150 *** (-3.19)	0.029 (0.23)
MTB	+			0.069 *** (5.56)	0.065 *** (5.37)	0.071 ** (2.56)
VIX	-			-0.055 *** (-7.78)	-0.056 *** (-7.90)	-0.053 *** (-7.80)
Intercept	?	0.383 *** (4.27)	0.384 *** (4.28)	0.936 *** (4.49)	0.948 *** (4.52)	0.782 *** (3.85)
Year-fixed effets		Yes	Yes	Yes	Yes	Yes
Country-fixed effects		Yes	Yes	Yes	Yes	Yes
Firm-fixed effects		No	No	No	No	No
Clustered standard errors		firm	firm	firm	firm	firm
R^2		0.4131	0.4168	0.4420	0.4403	0.5927
adjusted-R^2		0.3989	0.4025	0.4275	0.4256	0.5686
N		2298	2298	2298	2298	859
# Firms		291	291	291	291	126
# Countries		44	44	44	44	34
# Years		10	10	10	10	10

This table reports coefficient estimates and, in parentheses, t-statistics of Eq. (2.1), which, in column (2), regresses returns for the 12 months ending 3 months after the fiscal year end (*RET*) on net income excluding OCR gains and losses (*NIBOCR*), OCR gains and losses (*OCRGL*), and other comprehensive income (*OCI*). Column (1) shows a benchmark regression of *RET* on net income (*NI*) and *OCI*. Colum (3) shows regression results of Eq. (2.1) controlling for bank characteristics (*SIZE*, *LEV*, and *MTB*) and differences in the market risk across time (*VIX*). In addition, column (4) separates *NIBOCR* into interest income (*INTEREST*) and net income excluding own credit risk result and excluding interest income (*NIBOCRBINT*). Column (5) shows a subsample regression of Eq. (2.1) limiting our sample to bank-year that exercise the fair value option for financial liabilities. *SIZE* is the natural logarithm of total assets; *LEV* is total liabilities divided by total assets; *MTB* is market value of equity divided by the book value of equity; and *VIX* is the Chicago Board Options Exchange S&P 500 Volatility Index at each calendar year end. All variables are winsorized at the 0.5% and the 99.5% levels. All variables except the four control variables are scaled by beginning-of-year market value of equity. All regressions include year-fixed, country-fixed effects, and standard errors are robust and clustered by firms. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively (two-sided).

Table 2.5: Value Relevance of OCR Gains and Losses

Dependent variable:		*P*	*P*
Variables	Predicted sign	(1)	(2)
HFTA	+	0.856 ***	0.887 ***
		(3.40)	(3.14)
FVOA	+	1.064 ***	1.028 ***
		(4.07)	(3.88)
AFS	+	0.817 ***	0.794 ***
		(3.22)	(3.14)
OA	+	0.636 ***	0.875 ***
		(3.09)	(3.55)
HFTL	-	-0.936 ***	-0.950 ***
		(-3.43)	(-3.33)
FVOL	-	-0.903 ***	-0.883 ***
		(-3.71)	(-3.57)
OL	-	-0.675 ***	-0.877 ***
		(-3.12)	(-3.34)
NI	+	2.162 *	
		(1.94)	
NIBOCR	+		0.814 **
			(2.15)
OCRGL	**?**		**-8.599 ****
			(-2.19)
Intercept	?	27.860 ***	25.708 ***
		(5.11)	(5.29)
Year-fixed effets		Yes	Yes
Country-fixed effects		Yes	Yes
Firm-fixed effects		No	No
Clustered standard errors		firm	firm
R^2		0.9387	0.8800
adjusted-R^2		0.9370	0.8767
N		2243	2243
# Firms		291	291
# Countries		44	44
# Years		10	10

This table reports coefficient estimates and, in parentheses, t-statistics of Eq. (2.2) in column (2). We regresses market value of equity 3 months after the financial year end (*P*) on assets, liabilities—both separated into different financial instrument categories—and net income. *HFTA* (*HFTL*) are held-for-trading assets (liabilities) plus other derivative assets (liabilities). *FVOA* (*FVOL*) and *AFS* are fair-value-option assets (liabilities) and available-for-sale assets, respectively. *OA* (*OL*) are non-financial assets (liabilities) and financial assets (liabilities) at amortized cost. *NI* is total net income. *NIBOCR* is the net income excluding own credit risk gains and losses. *OCRGL* is the own credit risk gains and losses. We scale all variables by the number of common shares outstanding and express all amounts in U.S. Dollars. To avoid bias from extreme outliers, we eliminate observations that have absolute value of studentized residuals greater than 2. All regressions include year-fixed and country-fixed effects, and standard errors are robust and clustered by firms. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively (two-sided).

Table 2.6: Risk Relevance of OCR Gains and Losses

Dependent variable:		*σ(RET)*				*MM_Beta*	*LT_IR_Beta*
Variables	Predicted sign	(1)	(2)	(3)	(4)	(5)	(6)
σ(NIBOCR)	+	0.004 **			0.001	0.002	0.002
		(2.12)			(0.49)	(0.18)	(0.32)
σ(OCRGL)	**?**			**0.222 ****	**0.229 ****	**1.594**	**0.810**
				(1.97)	**(2.01)**	**(1.43)**	**(1.57)**
σ(OCI)	+		0.004 ***		0.003 ***	0.003	0.004
			(6.84)		(4.45)	(0.42)	(0.93)
SIZE	+	0.001	0.001	0.000	0.000	0.080 ***	0.013 **
		(0.39)	(0.51)	(0.08)	(0.06)	(6.91)	(2.32)
LEV	+	-0.006	-0.008	-0.007	-0.009	-0.271 *	-0.166 *
		(-0.27)	(-0.35)	(-0.29)	(-0.36)	(-1.92)	(-1.89)
MTB	-	-0.005 **	-0.005 **	-0.005 **	-0.005 **	-0.003	0.006
		(-2.46)	(-2.37)	(-2.53)	(-2.19)	(-0.20)	(0.67)
VIX	+	0.005 ***	0.005 ***	0.005 ***	0.005 ***	-0.010	0.050 ***
		(6.65)	(6.96)	(6.60)	(6.89)	(-1.62)	(9.11)
Intercept	?	-0.006	-0.009	0.000	-0.002	0.499 ***	-0.622 ***
		(-0.28)	(-0.42)	(0.01)	(-0.09)	(2.97)	(-5.25)
Year-fixed effets		Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects		Yes	Yes	Yes	Yes	Yes	Yes
Firm-fixed effects		No	No	No	No	No	No
Clustered standard errors		firm	firm	firm	firm	firm	firm
R^2		0.5518	0.5593	0.5455	0.5656	0.6337	0.5245
adjusted-R^2		0.5320	0.5399	0.5254	0.5456	0.6169	0.5046
N		1208	1208	1208	1208	1208	1070
# Firms		252	252	252	252	252	222
# Countries		43	43	43	43	43	33
# Years		6	6	6	6	6	6

This table reports coefficient estimates and, in parentheses, t-statistics of Eq. (2.3) in different specifications. We regresses one of three stock-market-based risk measures (SMR) on income volatility measures and control variables. We use standard deviation of raw returns (*σ(RET)*); market model beta (*MM_Beta*); and the absolute value of long-term interest rate betas (*LT_IR_Beta*) as our stock-market-based risk measures. All three risk measures are calculated over each of the six 60-month periods ending with the last month of each year 2010–2015. For our income volatility measures we, first, separate comprehensive income into other comprehensive income, net income excluding periodical OCR results, and periodical OCR results. Second, we calculate the standard deviation of all three comprehensive income components over each of the six 60-month periods ending with the last month of each year 2010–2015 (*σ(NIBOCR)*, *σ(OCRGL)* and *σ(OCI)*). We use control variables for differences in bank characteristics (*SIZE*, *LEV*, and *MTB*) and differences in the market risk across time (*VIX*). *SIZE* is the natural logarithm of total assets; *LEV* is total liabilities divided by total assets; *MTB* is market value of equity divided by the book value of equity; and *VIX* is the Chicago Board Options Exchange S&P 500 Volatility Index at each calendar year end. All variables are winsorized at the 0.5% and the 99.5% levels of their distribution. All income volatility variables are scaled by beginning-of-year market value of equity. All regressions include year-fixed and country-fixed effects, and standard errors are robust and clustered by firms. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively (two-sided).

Table 2.7: Return Relevance and Institutional Factors

Dependent variable:		*RET*	*RET*	*RET*	*RET*
Variables	Predicted sign	(1)	(2)	(3)	(4)
NIBOCR	+	0.058 ***	0.058 ***	0.058 ***	0.057 ***
		(2.89)	(2.89)	(2.89)	(2.85)
OCRGL	?	**-2.787 *** **	**-2.324 ** **	**-2.977 *** **	**-2.568 *** **
		(-4.07)	**(-1.98)**	**(-3.29)**	**(-3.45)**
HIGH_ANACOV	?		-0.028 *		
			(-1.66)		
HIGH_ANACOV*OCRGL	?		**-0.782**		
			(-0.56)		
MARKET_BASED	?			0.108	
				(1.57)	
MARKET_BASED*OCRGL	?			**0.542**	
				(0.44)	
IO	?				-0.032 *
					(-1.73)
IO * OCRGL	?				**-1.081**
					(-0.73)
OCI	+	0.040 ***	0.039 ***	0.040 ***	0.040 ***
		(3.14)	(3.13)	(3.14)	(3.08)
SIZE	?	0.004	0.007	0.004	0.004
		(0.86)	(1.28)	(0.86)	(0.75)
LEV	-	-0.169 ***	-0.183 ***	-0.169 ***	-0.165 ***
		(-3.64)	(-4.03)	(-3.63)	(-3.53)
MTB	+	0.069 ***	0.069 ***	0.069 ***	0.069 ***
		(5.56)	(5.61)	(5.56)	(5.56)
VIX	-	-0.055 ***	-0.054 ***	-0.055 ***	-0.055 ***
		(-7.78)	(-7.46)	(-7.77)	(-7.74)
Intercept	?	0.936 ***	0.914 ***	0.828 ***	0.935 ***
		(4.49)	(4.28)	(4.81)	(4.50)
Year-fixed effets		Yes	Yes	Yes	Yes
Country-fixed effects		Yes	Yes	Yes	Yes
Firm-fixed effects		No	No	No	No
Clustered standard errors		firm	firm	firm	firm
R^2		0.4420	0.4425	0.4420	0.4426
adjusted-R^2		0.4275	0.4275	0.4273	0.4277
N		2298	2298	2298	2298
# Firms		291	291	291	291
# Countries		44	44	44	44
# Years		10	10	10	10

This table reports coefficient estimates and, in parentheses, t-statistics of an extended version of Eq. (2.1), which regresses returns for the 12-month period ending 3 months after the fiscal year end (*RET*) on net income excluding own credit risk gains and losses (*NIBOCR*), own credit risk gains and losses (*OCRGL*) different interaction terms that capture differences in investor sophistication, other comprehensive income (*OCI*), and control variables (*SIZE*, *LEV*, *MTB*, and *VIX*). Investor sophistication is captured by *HIGH_ANACOV*, *MARKET_BASED*, *IO*, and all their respective interaction terms with *OCRGL*. *HIGH_ANACOV* is an indicator variable equal to one if analyst coverage is above median of all sample observations with non-zero *OCRGL; MARKET_BASED* is an indicator variable equal to one if the first principal component of two variables that measure the comparative activity and size of stock markets relative to banks is above median of all sample observations with non-zero *OCRGL* (Beck and Levine,2002 and Fiechter and Novotny-Farkas, 2017); and *IO* is an indicator variable equal to one if firms have non-zero shares held by investment firms. *SIZE* is the natural logarithm of total assets; *LEV* is total liabilities divided by total assets; *MTB* is market value of equity divided by the book value of equity; and *VIX* is the Chicago Board Options Exchange S&P 500 Volatility Index at each calendar year end. All variables except for the investor sophistication variables (*HIGH_ANACOV, MARKET_BASED, IO*) are winsorized at the 0.5% and the 99.5% levels of their distribution. *NIBOCR*, *OCRGL*, and *OCI* are scaled by beginning-of-year market value of equity. All regressions include year-fixed and country-fixed effects, and standard errors are robust and clustered by firms. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively (two-sided).

Appendix 2

Appendix 2.A: Variable Definition

Variables	Indicator/ Continous	Definition
Return relevance		
RET	Cont.	Share return for the 12 months ending three months after the fiscal year end.
NI	Cont.	Net income scaled by the market value of equity three months after the fiscal year begins.
NIBOCR	Cont.	Net income scaled by the market value of equity three months after the fiscal year begins minus *OCRGL*.
NIBOCRBINT	Cont.	Net income scaled by the market value of equity three months after the fiscal year begins minus *OCRGL* and *INTEREST*.
INTEREST	Cont.	Interest income scaled by the market value of equity three months after the fiscal year begins.
OCRGL	Cont.	Periodical profit or loss due to changes in an entity's own credit risk scaled by the market value of equity three months after the fiscal year begins.
OCI	Cont.	Other comprehensive income is comprehensive income minus net income. Comprehensive income is approximated by the change in equity from year t-1 to year t plus cash dividends paid in year t plus decreases in outstanding common and preferred stock in year t minus the amount received from the sale of common and preferred stock in year t. Other comprehensive income is scaled by the market value of equity three months after the fiscal year begins.
Value relevance		
P	Cont.	The market value of equity three months after the financial year end scaled by the number of outstanding shares.
HFTA	Cont.	Held-for-trading assets and other derivative assets scaled by the number of outstanding shares.
FVOA	Cont.	Fair-value-option assets scaled by the number of outstanding shares.
AFS	Cont.	Available-for-sale assets scaled by the number of outstanding shares.
OA	Cont.	Total assets minus *HFTA*, *FVOA*, and *AFS* scaled by the number of outstanding shares. *OA* consist of financial assets not measured at fair value and non-financial assets.
HFTL	Cont.	Held-for-trading liabilities and other derivative liabilities scaled by the number of outstanding shares.
FVOL	Cont.	Fair-value-option liabilities scaled by the number of outstanding shares.
OL	Cont.	Total liabilities minus *HFTL* and *FVOL* scaled by the number of outstanding shares. *OL* consist of financial liabilities not measured at fair value and non-financial liabilities.
NI	Cont.	Net income scaled by the number of outstanding shares.
NIBOCR	Cont.	Net income scaled by the number of outstanding shares minus *OCRGL*.
OCRGL	Cont.	Periodical profit or loss due to changes in an entity’s own credit risk scaled by the number of outstanding shares. It is expressed as a profit or loss.
Risk relevance		
σ*(RET)*	Cont.	Standard deviation of raw returns over each of the six 60-month periods.
MM_BETA	Cont.	Market-model betas estimated by regressing bank stock returns on a market-wide index of value-weighted returns over each of the six 60-month periods.
LT_IR_BETA	Cont.	Interest-rate beta estimated by regressing stock returns on monthly changes in long-term government bond yields over each of the six 60-month periods (Flannery and James, 1984)
σ(NI)	Cont.	Standard deviation of net income over each of the six 60-month periods scaled by beginning-of-year market value of equity.
σ(NIBOCR)	Cont.	Standard deviation of net income minus *OCRGL* over each of the six 60-month periods scaled by beginning-of-year market value of equity.
σ(OCRGL)	Cont.	Standard deviation of *OCRGL* over each of the six 60-month periods scaled by beginning-of-year market value of equity.
σ(OCI)	Cont.	Standard deviation of *OCI* over each of the six 60-month periods scaled by beginning-of-year market value of equity.
Fundamentals		
SIZE	Cont.	Natural logarithm of total assets at the financial year end.
LEV	Cont.	Total liabilities divided by total assets at the financial year end.
MTB	Cont.	Market value of equity divided by the book value of equity at the financial year end.
VIX	Cont.	The Chicago Board Options Exchange S&P 500 Volatility Index at each calendar year end.
Additional analysis		
HIGH_ANACOV	Ind.	An indicator variable equal to one if analyst coverage is above median of all sample observations with non-zero pOCR, and zero otherwise.
MARKET_BASED	Ind.	An indicator variable equal to one if the first principal component of two variables that measure the comparative activity and size of stock markets relative to banks is above median of all sample observations with non-zero pOCR (Beck and Levine,2002 and Fiechter and Novotny-Farkas, 2017).
IO	Ind.	An indicator variable equal to one if firms have non-zero shares held by investment firms.
FVOLBOCR	Cont.	Fair-value-option liabilities scaled by the number of outstanding shares minus *OCR_CUM*.
OCR_CUM	Cont.	The cumulative adjustements of fair-value-option liabilities due to changes in an entity’s own credit risk scaled by the number of outstanding shares. It is expressed as a change in the amount of liability.

Chapter 3: Beyond IFRS:
How Firms Benefit from Industry-Specific Reporting Guidance

(In collaboration with Jérôme Halberkann)

3.1. Introduction

The worldwide establishment of International Financial Reporting Standards (IFRS) is one of the most important developments in the history of accounting. Over 100 jurisdictions currently require application of IFRS for listed entities. The objectives underlying IFRS are to enhance comparability among financial statements and improve financial transparency with a uniform global set of standards directed towards the common information needs of a wide range of users (EC Regulation No. 1606/2002). This one-size-fits-all approach has limitations if investors demand industry-specific accounting information. IFRS figures may not cover all important financial aspects in an industry or may allow leeway that leads to unnecessary variation detrimental to transparency. To address these issues and to bridge the gap between IFRS figures and investors' information needs, the European Public Real Estate Association (EPRA) develops and issues Best Practice Recommendations (BPR). The EPRA BPR are intended to improve transparency, comparability, and relevance of published results to attract investments into listed European real estate companies (EPRA, 2014). EPRA-BPR-consistent information is based on IFRS figures and is complementary to IFRS financial statements, rather than substitutional.

In this paper, we seek to examine the usefulness, the economic effects, and the determinants of EPRA BPR compliance. More specifically, we investigate whether EPRA BPR disclosures are able to convey useful information that is incorporated into stock prices; whether EPRA BPR disclosures can be associated with positive capital market effects such as higher liquidity, lower cost of capital, and higher analyst following that go beyond the effects of applying IFRS; and whether certain factors favor an EPRA BPR adoption. Positive capital market outcomes are not an obvious result of additional disclosure, as additional disclosure can consist of boilerplate language, repetitions, or immaterial information that may reduce transparency and increase complexity (Lang and Stice-Lawrence, 2015). In addition, previous literature finds evidence that voluntary non-standardized disclosure exhibits positive capital market effects only for firms in weak information environments (e.g. Lang and Lundholm, 1993; Botosan, 1997; and Hail, 2002). We, however, focus on an arguably ex-ante rich information environment of listed European real estate companies that all apply IFRS. In addition, our study separates itself from previous research by focusing on voluntary *standardized* disclosure. We consider the information standardized because EPRA does not only issue recommendations on *what* information should be provided (e.g. performance measures, rental data, and valuation data) but also on *how* performance measures have to be calculated and how complementary information should be presented. The high level of detail in these recommendations is intended to increase consistency, and therefore transparency and comparability among listed European real estate firms. Capital market effects may, however, not be born out because application of EPRA BPR is voluntary and disclosure in accordance with EPRA BPR is neither enforced nor audited.

We choose to investigate EPRA BPR because this setting provides several unique advantages. First, companies within the real estate sector have similar operating activities and homogeneous financial statement structures, where investment properties represent a major part of total assets. Second, listed European listed real estate companies have the opportunity to follow voluntary industry-specific BPR. Compared to country-specific BPR, industry-specific BPR minimize unrelated cross-industry variation. Third, the staggered adoption of EPRA BPR by many European listed real estate companies and the continuous improvements in compliance by already EPRA-BPR-applying companies provide a strong setting to isolate potential effects of EPRA BPR adoption from concurrent events. Finally, the sample of European listed real estate companies is economically material as our sample consists of more than 100 companies with an aggregate market capitalization of over €190 billion.

Our research design is structured as follows: First, we investigate whether information in accordance with EPRA BPR is able to bridge the gap between IFRS figures and investors' information needs. More specifically, we investigate whether three EPRA performance measures (EPRA EPS, EPRA NAV, and EPRA NNNAV) are relatively and incrementally relevant in explaining variation in stock prices compared to pure IFRS figures (EPS and book value of equity).

Second, we investigate whether voluntary application of EPRA BPR is associated with positive capital market outcomes such as higher liquidity (bid-ask spread), lower refinancing costs (cost of capital), and better information environment (analyst coverage). We use three measures to capture the degree of compliance with EPRA BPR: (1) We count the number of disclosed EPRA performance measures in an annual report (*EPRA Performance Measures*); (2) we create a score that captures to which extent firms comply with all the EPRA BPR, including not only EPRA performance measures but also general recommendations and investment property reporting (*EPRA overall score*); and (3) we define an indicator variable equal to one if a firm's annual report was awarded a medal in the Annual Report Survey conducted by Deloitte and the EPRA (*medal*).

A central issue we encounter in our analysis is that some firms have been complying with the EPRA BPR before our sample period starts in 2009 whereas other firms have never started complying with EPRA BPR to any degree until the end of the sample period in 2013. Hence any association between the degree of compliance with EPRA BPR and capital market outcomes primarily sheds light on the characteristics of EPRA complying firms. To tackle this issue, we proceed with our analysis by restricting our sample to firms that have become compliant to EPRA BPR during the sample period, i.e., firms for which we have observations before and after EPRA BPR adoption. That way we are able to measure whether changes in EPRA BPR adoption are associated with changes capital market outcomes. In a second step, we restrict our overall sample to firms that switched back from being compliant to being non-compliant during the sample period. We conjecture that if there is a positive relation between the degree of EPRA BPR compliance and positive capital market outcomes, we should also be able to detect negative capital market effects if firms switch back from EPRA BPR compliance to non-compliance.

Third, we investigate whether there are certain conditions under which EPRA BPR adoption is favorable. Firms that consider EPRA BPR adoption face the question whether the benefits of an adoption outweigh the costs. If the costs outweigh the benefits, firms do not voluntarily adopt EPRA BPR. Those net benefits may vary across time and settings.

Based on a sample of 528 firm-year observations between the financial year 2009 and 2013, we find that net asset value (EPRA NAV) and triple net asset value (EPRA NNNAV) are relatively and incrementally value relevant. However, earnings per share based on EPRA BPR are neither relatively nor incrementally value relevant. Hence EPRA NAV and EPRA NNNAV seem to provide information that more closely reflect market capitalization than the traditional IFRS book value of equity.

In terms of capital market outcomes, firms committing to EPRA BPR are associated with increased liquidity, lower refinancing costs, and greater analyst coverage. By restricting our sample to firms that went from non-application (no medal) or low-level application (bronze medal) to application (silver or gold medal) within our sample period, we find that the staggered adoption of EPRA BPR is associated with an increase in liquidity and an increase in analyst coverage but fail to find any effect on the cost of capital. In addition, we find that the switch back—from application to non-application or low-level application—is associated with a decrease in liquidity and a decrease in analyst coverage but, again, fail to find any effect on the cost of capital.

Lastly, we find that an upcoming debt offering provides incentives for real estate firms to adopt EPRA BPR. In addition, firms with upcoming debt offerings, firms in countries with better legal quality, firms with lower stock volatility, and firms with weaker stock price performance tend to more strongly comply with EPRA BPR. The negative association between stock price performance and the degree of compliance with EPR BPR mitigates concerns that positive capital market outcomes would only be a result of better firm performance that might be positively correlated with higher EPRA BPR compliance.

Our study contributes to the literature at least in the following three aspects. First, we extend the current disclosure literature, which has largely focused on capital market effects of IFRS adoption in Europe, to industry-specific financial disclosure beyond IFRS. Second, whereas prior literature on voluntary disclosure beyond IFRS focused on non-standardized disclosure, which may introduce boilerplate language, repetitions, immaterial information, and inconsistencies into annual reports that can reduce transparency and increase complexity, we investigate a stronger setting where voluntary disclosures are standardized by the EPRA. Third, we focus on a sample of firms in an arguably ex-ante strong information environment with ex-ante high liquidity, low cost of capital, and high analyst coverage. Previous literature has detected significantly positive capital market outcomes only for voluntary financial disclosures in week information environments.

The remainder of the study is as follows. Section 3.2 reviews the related empirical and theoretical literature on the relation between disclosures and capital market outcomes. Section 3.3 outlines the EPRA BPR. Section 3.4 develops the hypotheses. Section 3.5 describes the sample selection process, the disclosure scores, and presents summary statistics. Section 3.6 describes the research design and presents the results. Section 3.7 concludes.

3.2. Prior Literature

3.2.1. Voluntary Non-Standardized Disclosure

Before the mandatory IFRS adoption in the European Union in 2005, extensive academic research had been conducted to determine whether complementary voluntary disclosure leads to positive capital market effects. Theoretical models suggest that additional disclosure may alleviate information asymmetries between investors, resulting in a smaller premium (discount) at which they are willing to sell (buy) shares to protect themselves from better informed investors acting on private information (Kim and Verrecchia, 1994). In addition, higher level of disclosure may also reduce a firm's cost of capital by attracting increased demand from large investors due to increased liquidity (e.g. Diamond and Verrecchia, 1991 and Baiman and Verrecchia, 1996). Lang and Lundholm (1996) investigate the determinants of voluntary disclosure and find that larger firms, firms with higher stock returns, and firms undertaking equity or debt offerings have higher level of disclosure than their counterparts. Welker (1995) adds that simultaneity may well exist between the firm's choice of disclosure policy and investors' assessments of the information asymmetry. He finds that firms with disclosure rankings in the bottom third of the empirical distribution have spreads that are approximately 50% higher than firms in the top third. Healy, Hutton, and Palepu (1999) extend the analysis of Welker (1995) and find that, in addition to stock liquidity, voluntary disclosure is accompanied by improved stock performance, increased institutional ownership, and more analysts following. Sengupta (1998) investigates the link between disclosure quality and the firm's cost of debt financing and finds a negative association between the two. The aforementioned empirical results are all based on analyst ratings of the firm's overall disclosure policy by the Association for Investment Management and Research (AIMR). The AIMR metric measures disclosure quantity through a broad range of channels including analyst meetings and conference calls. However, the metric has several limitations: The rankings are only available for a subset of large U.S. firms during the 1980s and 1990s. Since the disclosure levels are positively correlated with firm size (Lang and Lundholm, 1993), AIMR firms are unlikely to display sufficient cross-sectional variation in disclosure levels to make strong and generally applicable inferences (Botosan, 1997). In addition, it is unclear how frequent and at which point in time the AIMR metric is reassessed. For example, Healy, Palepu, and Sweeney (1995) are able to identify only 90 large and sustained increases in AIMR disclosure rankings in a sample of 595 firms in 23 countries over the period 1980 to 1990. It is also unclear whether analysts on the AIMR panels take the ratings seriously, how they select firms to be included in the ratings, and what bias they bring to the rating (Healy and Palepu, 2001). Due to those concerns, Botosan (1997) constructs an own disclosure index to measure the association between disclosure level and the cost of equity capital. She focuses on the year 1990 and a relatively small sample of 122 observations from the machinery industry to measure within-industry variation. She finds a negative association between disclosure levels and the cost of equity capital for firms with low analyst following. However, the results do not extend to firms with high analyst following. Similarly, Hail (2002) investigates the association between voluntary disclosures and the cost of equity capital in an environment where firms had considerable reporting discretion and mandated level of disclosure was low. His sample comprises 73 non-financial Swiss companies. Mitigating self-selection bias by using a 2SLS approach, he generally finds a negative association between voluntary disclosures and the cost of capital. Francis, Nanda, and Olsson (2008) point out that it is not obvious that greater voluntary disclosure should lead to lower information asymmetry. Earlier theoretical research had shown that additional voluntary disclosure may lead to a more asymmetric information environment than would exist in their absence (Kim and Verrecchia, 1994 and Zhang, 2001). Francis, Nanda, and Olsson (2008) argue that the association between voluntary disclosures and cost of capital may be largely driven by omission of correlated earnings quality. They use a self-constructed disclosure index, based on the disclosure index by Botosan (1997) and increase the sample size from 122 observations to 677 sample firms in one year (2001). They find that the relation between voluntary disclosures and the cost of capital is substantially reduced when they control for earnings quality. However, it remains unclear whether earnings quality drives voluntary disclosure, vice versa, or whether the proxy for voluntary disclosure just measures the same as the proxy for earnings quality. Overall, both the AIMR and the self-constructed disclosure score by Botosan (1997) are weak proxies for complementary financial measures as the AIMR score lacks cross-sectional variation in disclosure levels and is skewed towards large companies (Botosan, 1997).

More recent literature tries to address the selection problem when investigating the economic outcomes of voluntary disclosure. Balakrishnan et al. (2014) is a recent study that sheds light on the causality of voluntary disclosure—in the presence of IFRS—on liquidity. They exploit a natural experiment that uses 43 closings of brokers during 2000 and 2008 as an exogenous shock to analyst coverage. Measuring voluntary disclosure in the form of guidance regarding their quarterly EPS numbers, they find that the reduced liquidity after a coverage shock can recover faster if firms have a history of providing increased disclosure. They also show that the benefit of voluntary disclosure is economically significant and that failure to control for endogeneity of voluntary disclosure seriously biases estimate of the beneficial effect of disclosure on liquidity downwards. Similarly, Guay, Samuels, and Taylor (2016) find that managers respond to exogenous increases in financial statement complexity—measured by the readability and length of 10-K fillings—by increasing voluntary disclosure. Schoenfeld (2017) uses the inclusion in the S&P 500 index as an exogenous shock to disclosure and stock liquidity where managers can hardly influence the ownership level assumed by the index fund—as it is a function of assets under management—and where managers cannot influence the timing of the inclusion. Schoenfeld (2017) finds that voluntary disclosure increases with the level of index fund ownership. Using a recursive structural equation model, he finds that part of the increase in liquidity can be explained by the increase in voluntary disclosure.

3.2.2. Disclosure in Accordance with IFRS

Instead of measuring the relationship between voluntary disclosure and potential capital market outcomes directly, another stream of literature focuses on the association between voluntary IFRS adoption and capital market outcomes. Although IFRS prescribes not only the content of information that have to be disclosed but also the recognition and measurement of financial statement items, the effect of voluntary IFRS adoption on capital market outcomes may partly be driven by the disclosure component. The strength of the IFRS setting is that switching from a local standard to IFRS cannot easily be reversed and, thus, represent a strong commitment device to disclosure in the future (Leuz and Verrecchia, 2000). Leuz and Verrecchia (2000) focus on Germany, a country with a relatively low disclosure level within the sample period, and investigate firms that had switched from German GAAP to either IFRS or U.S. GAAP. They find that voluntary IFRS or U.S. GAAP adoption leads to lower information asymmetry as measured by the bid-ask spread and share turnover compared to compliance with German GAAP. In addition, Leuz (2003) finds that the bid-ask spread and the share turnover of German firms that voluntarily adopt IFRS are not significantly different from those that voluntarily adopt U.S. GAAP. Daske (2006) extends the analysis in Leuz and Verrecchia (2000) to the cost of capital and analyzes this association for a German sample in the period between 1993 and 2002. He finds no significant relation between the cost of capital and the adoption of either IFRS or U.S. GAAP. Similarly, Cuijpers and Buijink (2005) also fail to find a relation between the cost of capital and the adoption of either IFRS or U.S.

GAAP for a broader European sample. However, they find a positive association between analysts following and the adoption. Daske et al. (2013) partition voluntary IFRS adopters into serious and label adopters.[29] They conclude that IFRS reporting does not constitute a commitment to increase transparency per se and that, on average, association between voluntary IAS adoption and market liquidity or the cost of capital is either insignificant or points in the wrong direction. In addition, they find that serious adopters—experiencing substantial changes in their reporting incentives around IFRS adoption—show a significant increase in market liquidity and a decrease in cost of capital relative to label adopters.

When IFRS became mandatory for listed firms in the European Union, it attracted much attention by academics. A large set of literature documents positive capital market effects such as higher stock liquidity (e.g. Daske et al., 2008), lower cost of capital (e.g. Daske et al., 2008 and Li, 2010), lower forecast errors and forecast dispersion (e.g. Byard, Li, and Yu, 2011), and higher foreign investments (DeFond et al., 2011 and Khurana and Michas, 2011). However, Daske et al. (2008), Byard, Li, and Yu (2011), and Shima and Gordon (2011) note that the positive capital market effects are conditional on countries with strict enforcement regimes or strong incentives to be transparent. These findings raise concerns whether the results are driven by concurrent reporting and enforcement changes or are indeed the result of mandatory IFRS adoption. In addition, Daske et al. (2008) document an increase in market liquidity for voluntary IFRS adopters in the year when IFRS became mandatory in the European Union. They argue that one potential explanation for this capital market effect is that voluntary adopters benefit from an increased set of comparable firms, which in turn could lead to improved risk sharing across a large set of investors. However, they find no significant results that would underline this theory. They, however, find evidence that the effect stems from concurrent institutional changes. Voluntary adopters likely have better reporting

[29] Serious adopters change their reporting policy as a result of adopting IFRS whereas label adopters make no material change to their reporting policy.

incentives to begin with and, hence, should be more responsive to institutional changes like the mandatory IFRS adoption. Christensen, Hail, and Leuz (2013) extend the analysis of Daske et al. (2008) and find that mandatory IFRS reporting, on average, had little impact on liquidity. Their analysis shows that observed liquidity effects are unrelated to the enforcement level and legal quality of the countries but are concentrated in EU countries only. Overall, they suggest that that enforcement changes in a few EU countries play a critical role for the previously documented liquidity effects but they do not rule out that IFRS still plays a critical role in combination with those changes in enforcement regulations.

Overall, using (voluntary) IFRS adoption as a shock to (voluntary) disclosure initially seemed like a strong setting to identify potential capital market effects. However, concurrent enforcement changes in the EU made it difficult for researchers to disentangle the enforcement effect from the IFRS effect. Even if we assumed that (voluntary) IFRS adoption affects capital market outcomes, we still cannot assign the effect exclusively to increased disclosure because IFRS provides rules that do not only mandate the disclosure of certain information but also the recognition and measurement of financial statement positions. Furthermore, we have no information whether the capital market effects can be generalized to all industries or whether IFRS is better suited to some industries than to others.

3.3. EPRA and the Real Estate Industry

The EPRA was founded in 1999 to represent the interests of the European public real estate sector. More specifically, the association is intended to foster investments into the real estate sector by issuing and frequently updating BPR. Those EPRA BPR were originally developed to provide real estate companies with “additional guidance on how to interpret and apply IFRS accounting consistently across Europe” (EPRA, 2010). With the establishment of

IFRS, the focus moved to the disclosure of key performance indicators that were seen to be of most relevance to investors. These EPRA performance measures form an industry-wide set of financial reporting key performance indicators (KPIs) that are building on the reporting figures published in IFRS reports. As such, they are intended to be a complement to IFRS rather than a substitute. They share a goal similar to IFRS by striving to make the financial statements of public real estate companies “clearer, more transparent, and comparable across Europe” (EPRA, 2010). EPRA BPR state that these additional disclosures are useful because financial statements under IFRS do not provide stakeholders with the most relevant information to assess the firm’s operating performance (EPRA, 2014).

EPRA BPR define six performance measures. (i) EPRA Earnings are intended to provide a measure of the performance of the property portfolio. They exclude, among others, changes in the values of investment properties as well as profits and losses on disposal thereof. These profits and losses are considered not to be relevant to the recurring performance of the portfolio and should therefore not affect EPRA EPS. Instead, EPRA EPS focuses on recurring items such as rental income, property expenses, and personnel expenses.

(ii) The EPRA Net Asset Value (NAV) is a measure for the fair value of the property portfolio. Compared to the NAV per the financial statements, which firms usually approximate by the book value of equity, the EPRA NAV incorporates all revaluations of investment properties, tenant leases, and trading properties that are held at amortized cost on the balance sheet. It, thus, accounts for differences in the valuation models applied across firms and provides an industry-wide more comparable measure of the property portfolio. In addition, EPRA NAV excludes the fair value of financial instruments, deferred taxes, and goodwill related to deferred taxes.

To provide information on the fair value of *all* assets and liabilities of the firm, (iii) the EPRA Triple Net Asset Value (NNNAV) also includes the fair value of financial instruments, the fair value of debt, and deferred taxes.

EPRA BPR define furthermore (iv) the EPRA Net Initial Yield (NIY) and (v) the EPRA Vacancy Rate, two KPIs that show considerable variation and inconsistencies across real estate firms if they do not comply with EPRA BPR. In July 2013, EPRA BPR added (vi) the cost ratio as a sixth measure, which is intended to provide a base-line from which further, more detailed information on costs can be disclosed.

To further improve the usefulness of disclosed figures, EPRA BPR advise the use of an external appraiser on at least an annual basis who values the firm's properties in accordance with the International Valuation Standards. The names of the valuation firms as well as the basis of the fees are also recommended to be disclosed. Additional recommended disclosures include a list of the major properties owned, information on the development program, and like-for-like rental growth measures. The EPRA BPR are updated almost on a yearly basis where small changes and additions are made, tailored to investors' needs and demands.

Once a year, Deloitte and the EPRA issue gold, silver, and bronze accreditations in their EPRA Annual Report Survey to companies implementing EPRA BPR. In 2014, 50% of the companies in the survey received an award. 25 companies received a gold award, 9 a silver award, and 8 a bronze award (Deloitte and EPRA, 2014). According to the Deloitte and EPRA (2014), 81% disclosed at least one EPRA performance measure and 33% disclosed all 6 performance measures. EPRA BPR has gained considerable momentum in the last years and can be considered well established in the European real estate sector as of mid-2015.

3.4. Hypothesis Development

Prior literature finds evidence indicating that serious voluntary and mandatory IFRS adoption is associated with higher liquidity and lower cost of capital when combined with a high enforcement environment. Although previous research trying to establish a causal relation between IFRS reporting and positive economic outcomes face major challenges (e.g. self-selection bias for voluntary adoption or concurrent events during mandatory IFRS adoption around Europe), the findings still empirically underpin the general consensus that financial statements prepared in accordance with IFRS provide information that is valuable to investors. The value of IFRS figures may vary from industry to industry though, as the types of measures relevant for equity valuation are context dependent (e.g., Daske et al., 2008; Armstrong et al., 2010; Byard, Li, and Yu, 2011; and Horton, Serafeim, Serafeim, 2013). For some sectors, IFRS may not provide measures specific enough to fully cover investors' information needs. IFRS figures may either offer measurement leeway that impairs comparability across firms, may be computed in a way that is not directly useful to investors, or may be missing. In these sectors, voluntarily disclosing additional information cannot completely solve the problem because unstandardized figures may still show considerable variation and inconsistency across firms and, hence, lack comparability. This issue might explain the mixed results in empirical studies on the benefits of voluntary unstandardized disclosure (e.g., Botosan, 1997 and Francis, Nanda, and Olsson, 2008).

Standardization of voluntary information can be achieved by sector guidance on voluntary disclosures. In the European real estate sector, such guidance has been developed by the EPRA. Those sector guidance (i.e., EPRA BPR) aim to bridge the gap between IFRS figures and investor's information needs to attract investments in the real estate sector through consistent and relevant complementary information. This objective leads us to our first hypothesis:

H_1: EPRA BPR figures provide information useful to investors.

We investigate the economic consequences of EPRA BPR adoption. Specifically, we are interested in the association between EPRA BPR disclosures and capital market outcomes such as stock liquidity, cost of capital, and analyst following. Better disclosure can decrease information asymmetry between holders and potential buyers of firm shares and, thus, reduce adverse selection. The reduction in adverse selection decreases the bid-ask spread, as buyers demand a lower premium to trade with potentially better informed sellers (Kim and Verrecchia, 1994 and Leuz and Verrecchia, 2000). Similarly, better disclosure can reduce a firm's cost of capital by attracting investors and, hence, increasing the liquidity of its securities. Put differently, to attract investors into less liquid securities, issuers must issue capital at a discount (Diamond and Verrecchia, 1991 and Leuz and Verrecchia, 2000). The theoretical relation between amount of disclosure and the number of analysts following, however, is ambiguous. Assuming analysts act primarily as *information intermediaries*, their job consists in collecting public information through different channels, processing them into a more concise and easier-to-absorb form, and transmitting them to the capital market. In such a system, an increase in the amount of information will increase the demand for analyst services and eventually increase the equilibrium number of analysts (Bhushan, 1989). However, if analysts act primarily as *information providers*, who distribute ex-ante private information to the capital market, an increase in firm-provided information will substitute for the analyst report (Lang and Lundholm, 1993). Empirically, Lang and Lundholm (1996) find evidence that analysts follow firms with higher disclosure quality. Dhaliwal et al. (2011) and Gao et al. (2016) document that analyst following increase with the initiation of CSR reports. We, thus, hypothesize:

H_2: Complying with EPRA BPR is associated with higher stock liquidity, lower cost of capital, and more analysts following.

Implementation costs are relatively high compared to future costs of maintaining EPRA-BPR compliance. Still the implementation costs of EPRA BPR are relatively low compared to IFRS adoption, as most of the information used for the EPRA BPR is already created in the process of preparing IFRS statements. Firms voluntarily adopt EPRA BPR only if they believe that benefits outweigh the costs. Moreover, the extent to which firms decide to comply with EPRA BPR may also vary.

For firms to clear the hurdle of the implementation costs, they need to face a situation where the EPRA BPR benefits seem particularly important. We conjecture that such a situation exists when firms need external financing. Thus, firms raising capital may choose to adopt EPRA BPR to improve the quality of their disclosure in an effort to reduce the cost of capital (Dhaliwal et al., 2011 and Gao et al., 2016). In addition, managers may provide more information to investors to explain poor performance (Leuz and Wysocki, 2016).

H_{3A}: Firms expanding or planning to expand their investor basis are more likely to adopt EPRA BPR.

H_{3B}: Firms expanding or planning to expand their investor basis comply to a greater extent with the EPRA BPR.

3.5. Sample Selection, Disclosure Score, and Summary Statistics

3.5.1. Sample Selection Process

Table 3.1 outlines the sample selection process. We construct our sample from the constituent list of the FTSE EPRA/NAREIT Developed Europe index as of November 19, 2014 (95).[30] Constituents of the FTSE EPRA/NAREIT Developed Europe index all disclose a full set of English Annual Accounts and derive at least 75% of their total EBITDA from ownership, trading, and development of income-producing real estate (EPRA, 2015). To increase the number of EPRA BPR adopters, we also include all European real estate companies from the list of EPRA Members as of December 20, 2014 (+26). We exclude firms for which annual reports are unavailable through the sample period (-9). This procedure results in 112 potential sample firms. The sample period spans five fiscal years starting in 2009 and ending in 2013 yielding 560 potential firm-year observations.[31] We eliminate firm-years in which firms are not publicly traded (-32), which might be the case if firms were inexistent at that time, merged with another company, or ceased their existence. Eventually, our sample comprises 528 firm-years. Depending on the regression models, additional observations were dropped from the sample because of missing values.[32]

To examine the effect of EPRA disclosure on capital market outcomes, we first hand-collect data from 528 annual reports on the degree of compliance with EPRA BPR. We use this data to construct our disclosure scores (*EPRA Overall Score* and *EPRA Performance Measures*). To complement these two scores, we examine the EPRA Annual Report Surveys as issued by Deloitte and the EPRA to gather information on a third-party disclosure score (*Medal*).

We draw data on forecast biases and analyst coverage from the Thompson Reuters I/B/E/S; data on debt and equity offerings from Thomson Reuters SDC Platinum; data on

[30] The FTSE EPRA/NAREIT Global Real Estate Index Series is the most widely used global benchmark for listed real estate companies.

[31] EPRA issued a significant revision of its BPR in July 2009 in which they extended the set of EPRA performance measures from three (EPRA EPS, EPRA NAV, and EPRA NNNAV) to six adding the EPRA Net Initial Yield, the EPRA 'topped-up' NIY, and the EPRA Vacancy Rate. In addition, they changed their approach in the EPRA Annual Report Survey in 2009. Rather than recognizing only a handful of best-in-class annual reports, they started awarding virtual medals to investment property companies that comply to a certain degree with the BPR.

[32] Our sample selection process leads to a sample that is closely related to the sample in Muller, Riedl, and Sellhorn (2011). We work with a sample of 121 firms that were active as of 2009 whereas Muller, Riedl, and Sellhorn (2011) identify 112 European real estate firms active as of 2006.

countries' legal quality from Kaufmann, Kraay, and Mastruzzi (2010); and financial data from Thomson Reuters Datastream. All variable definitions are presented in Appendix 3.A.

3.5.2. Disclosure Statistics and Score Construction

Table 3.2 provides descriptive statistics on the disclosure quality relating to investment property transactions. On average, we observe that firms spend 40.56 pages or 26% (40.56 ÷ 155.84) of their annual reports on financial statement notes. We count, on average, 23.97 occurrences of the word "EPRA" and 3.36 EPRA figures in the annual reports. The amount of EPRA figures disclosed increased significantly and gradually from 1.29 to 4.92 in our sample period. Firms use external appraisers, who assess the value of the assets at least once a year, in about 90% of the annual reports. The EPRA BPR endorse five tables in each annual report, disclosing certain information in a specific structure. However, only 0.25 tables are disclosed, on average, and untabulated statistics show that only 8% of the annual reports show at least one table. In comparison, untabulated statistics show that 65% of all annual reports disclose at least one EPRA performance figure suggesting that the tables are far less widespread across our sample than the disclosure of EPRA performance figures. 92% use a fair value approach for the measurement of investment property assets.

To measure the disclosure effort for a given real estate firm in a year, we compute three proxies. First, *EPRA performance measures* analyzes the number of EPRA performance measures a company reports in their annual reports. The EPRA figures consist of EPRA EPS, EPRA NAV, EPRA NNNAV, EPRA NIY, EPRA NIY 'topped up', EPRA vacancy rate, EPRA cost ratio including vacancy costs, and the EPRA cost ratio excluding vacancy costs. The former three figures should be disclosed on a per-share as well as on an absolute basis. As a result, there are 11 figures to be disclosed. Firms receive 1 point for each EPRA performance figure except for the vacancy rates, which is awarded 2 points (12P).[33] The total number of points is divided by 12 to scale the score between 0 and 1.

Second, we propose a broader proxy *EPRA overall score*. *EPRA overall score* can be separated into two parts: The number of EPRA performance measures a company reports in their annual reports—equal to *EPRA performance measures*—and the degree of additional disclosure in compliance with the EPRA BPR. Again, firms receive up to 12 points for the first part. In the second part regarding additional disclosure, we allocate 1 point for each of the following valuation techniques or disclosures in the annual report: a separate chapter in the annual report for the information in accordance with the EPRA BPR (1P), a list of the major properties owned (1P), a list of all development and redevelopment properties (1P), the standardized tables (5P; 1P for each table), the fair value change due to the new fair-value definition for non-financial assets in 2013 (1P), investment property assets valued by external appraisers within the last year (1P), report available in English (1P), and investment property assets recognized at fair value (1P).[34] In total, each company can reach up to 12 points for the first part and 12 points for the second part. The total number of points is divided by 24 to scale our score between 0 and 1. Table 3.2 summarizes the items that were considered with the corresponding weights.

To complement our results with a third-party disclosure score, we consider the virtual *medals* that are awarded each year by Deloitte and the EPRA based on a review of the firms' financial statements. Gold, silver, and bronze medals are awarded for reports scoring "exceptionally", "highly", and "well", respectively, based on compliance with EPRA BPR (Deloitte and EPRA, 2014). We observe that 30% of our firm-year observations have received

[33] Basically, there are six individual figures (EPRA EPS, EPRA NAV, EPRA NNNAV, EPRA NIY, EPRA vacancy rate, and EPRA cost ratio) that should be calculated in two different ways except for the EPRA vacancy rate. We award 2 points to each of those six individual figures.

[34] IFRS 13 – Fair Value Measurement is effective since 1 January 2013. It adopts a highest-and-best-use approach to the measurement of non-financial assets. The new definition affected investment property values. However, only a limited number of firms disclosed those changes that stem from the change in the definition.

an award in the EPRA Annual Report Survey for their disclosure. Firms that received a gold medal reported all six EPRA performance measures in a separate EPRA BPR section including calculations. However, a complete list of criteria that shaped Deloitte's and the EPRA's assessment of whether a firm should receive either a gold, silver, or bronze medal is not publicly available.

We define a binary variable *EPRA Application* equal to one for years in which the firm receives a silver or gold medal and 0 otherwise. We exclude bronze medals as these are the lowest awards and may not indicate compliance on a level high enough to lead to observable market reactions. Table 3.3 reports Spearman's rank (upper right corner) and Pearson's product-moment correlation (lower left corner) of market outcome variables and disclosure proxies. We find that our three main market outcome variables (i.e., *Log(Spread)*, *Log(COC)*, and *AnaCov*) are all significantly correlated with our main disclosure proxies (i.e., *Medal*, *EPRA Overall Score*, *EPRA Performance Measures* and *EPRA application*) and that all the correlation coefficients exhibit the expected signs. The correlation between *Log(COC)* and the disclosure proxies is noticeably smaller than for the other two main market outcome variables, which is in line with the fact that our proxy for cost of capital is a noisier and less direct measure than the proxy for liquidity and analyst coverage.

3.5.3. Summary and Distributional Statistics

Table 3.4 reports summary statistics on the 528 firm-year observations for all test variables (definitions of all variables are presented in Appendix 3.A). We observe that firms within our sample exhibit, on average, narrow spreads (0.47%), low cost of capital (7.65%), and a high number of analysts following (6.41).[35] Also, S*ize* exhibits that the market

[35] Charoenwong, Chong, and Yang (2014), for example, find an average spread of 0.87% for a broad sample of international firms from 1996 to 2010 compared to 0.47% in our sample. Hail and Leuz (2006) calculate a cost of capital of 12.49% for the period between 1992 and 2001 for a broad sample of international firms compared to 7.65% in our sample.

capitalization of the sample firms is, on average, large (EUR 0.63 billion) and *LegalQuality* exhibits that the legal system is, on average, strong (1.49).[36] Hence we focus on an ex-ante strong legal environment and a sample of firms that all comply with IFRS. We apply log-transformation to spread, cost of capital, returns, and size to make the positively skewed distributions more normal.

Table 3.5 reports distributional statistics for the measurement of investment property assets and three different disclosure scores. 92% (488 ÷ 528) of all firm-years apply the fair value approach for the measurement of investment properties while only 8% (40 ÷ 528) use the amortized cost approach. Disclosure is measured using the number of EPRA figures disclosed in the firm-year's annual report (*EPRA Performance measures*); a self-constructed overall score that measures the degree to which firms comply with the EPRA BPR (*EPRA overall score*); and an indicator variable equals to 1 if the firm received an award in form of a virtual medal in the firm-year's corresponding EPRA Annual Report Survey as issued by Deloitte and the EPRA, and zero otherwise (*Medal*).

Table 3.5, Panel A shows that firms are located in 16 different countries whereof 69% of all observations stem from the United Kingdom (31%), Germany (13%), France (10%), Sweden (8%), or Belgium (7%). The amortized cost approach is used only in five countries (Germany, France, Turkey, Spain, and Sweden).[37] Examining the average number of EPRA figures disclosed in an annual report, the average EPRA overall score, and the density of total medals per total observations, Belgium, Finland, France, the Netherlands, Switzerland and the United Kingdom can clearly be considered as *above average*. Hence 61% of the firm-year observations stem from high disclosure countries.

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[36] In comparison, legal quality within the United States in the same time frame was 1.36. Overall, Hong Kong (1.89) exhibits the highest coefficient whereas North Korea (-2.47) exhibit the lowest coefficient. Only eight out of 215 countries outside from our sample exhibit larger coefficients.

[37] Sometimes local laws and local exchange rules prohibit firms from using the amortized cost approach for the measurement of investment property assets.

Table 3.5, Panel B shows how the measurement of investment property assets and the three disclosure scores evolve over time. Whereas the percentage of firms that apply the amortized cost approach remains relatively constant, almost all three disclosure scores increase gradually over time. Untabulated descriptive statistics show that Pearson correlations between the three disclosure scores are all positive and significant at the 0.001 significance level.[38]

3.6. Empirical Analysis

3.6.1. Value Relevance

We begin our empirical analysis by investigating the *relative* and *incremental* value relevance of EPRA NAV per share, EPRA NNNAV per share, and EPRA EPS compared to IFRS book value of equity per share and IFRS EPS.[39] The significance of the relationship between disclosed accounting figures and share prices captures whether figures provide both relevant and reliable information to investors (Barth, Beaver, and Landsman, 2001). By regressing share prices on a set of different performance measures, we are able to evaluate the value relevance, and thus the decision usefulness of the information (Easton, Eddey, and Harris, 1993).

Following the approach by Barth and Clinch (1998), we regress price per share (*PPS*) on a measure of book value of equity per share (IFRS book value of equity, EPRA NAV, or EPRA NNNAV) and periodical performance per share (IFRS EPS or EPRA EPS). We use two specification of this model to measure *relative* and *incremental* value relevance. First, we investigate whether each of the different measures of book value of equity per share together

[38] Correlation between *EPRA Figures* and *EPRA Overall Score* is 0.9420; correlation between *EPRA Overall Score* and *Medal* is 0.6323; and correlation between *EPRA Figures* and *Medal* is 0.6605.

[39] Both IFRS EPS and EPRA EPS are on the basis of basic number of shares, i.e. not diluted.

with the measures of periodical performance per share are relatively value relevant. Therefore we specify the following model:

$$PPS_{i,t} = \beta_0 + \beta_1\, EQUITY\_VALUE_{,i,t} + \beta_2\, PERIODICAL\_PERFORMANCE_{i,t} + \varepsilon_{i,t}\,, \qquad (3.1A)$$

where *EQUITY_VALUE* is either IFRS book value of equity per share (*BVE_PS*), EPRA NAV per share (*EPRA_NAV_PS*), or EPRA NNNAV per share (*EPRA_NNNAV_PS*) and *PERIDICAL_PERFORMANCE* is either IFRS EPS (*EPS*) or EPRA EPS (*EPRA_EPS*).

Second, we extend the base model—as specified in Equation (3.1A) using *BVE_PS* and *EPS*—by adding the difference between EPRA NAV per share and IFRS book value of equity per share (*EPRA_NAV_PS – BVE_PS*) (Table 3.6, model 7) and the difference between EPRA NNNAV per share and book value of equity per share (*EPRA_NNNAV_PS – BVE_PS*) (Table 3.6, model 8), respectively. At the same time, we add the difference between IFRS EPS and EPRA EPS (*EPRA_EPS - EPS*) (Table 3.6, model 7 and 8). That way we are able to investigate whether the three EPRA figures provide *incremental* value-relevant information to investors.

To measure the incremental effects of all three EPRA figures, we specify the following model:

$$PPS_{i,t} = \beta_0 + \beta_1\, BVE\_PS_{i,t} + \beta_2\, (EPRA\_[NN]NAV\_PS_{i,t} - BVE\_PS_{i,t}) +$$
$$\beta_3\, EPS_{i,t} + \beta_4\, (EPRA\_EPS_{i,t} - EPS_{i,t}) + \varepsilon_{i,t}\,. \qquad (3.1B)$$

Table 3.6 reports regression results based on Equation (3.1A) and (3.1B). In our base model (1) we regress price per share on IFRS book value of equity per share and IFRS EPS. The coefficients estimates of 0.791 for *BVE_PS* and 2.564 for *EPS* are both statistically significant at the one-percent level and similar to other papers that use value-relevance methodology (e.g. Barth and Clinch, 1998; Landsman, Peasnell, and Shakespeare, 2008; and Goh et al., 2015).

Next, we replace IFRS book value of equity per share with the EPRA book value of equity per share, i.e. *EPRA_NAV_PS* and *EPRA_NNNAV_PS*. Model (2)-(3) and (5)-(6) show that both EPRA NAV and EPRA NNNAV are statistically significant at the one-percent level, therefore EPRA NAV and EPRA NNNAV are *relatively* value relevant. Replacing IFRS EPS with the EPRA EPS in models (4)-(6) leads to coefficient estimates with similar magnitude as the EPS. However, they are not statistically significant, except for model (5).

In addition, we find that *EPRA_NAV_PS – BVE_PS* and *EPRA_NNNAV_PS – BVE_PS* are statistically significant at the one-percent level in model (7) and (8), respectively, therefore EPRA NAV and EPRA NNNAV are *incrementally* value relevant. Investigating EPRA EPS, we find no evidence that EPRA EPS has incremental value relevance over EPS in model (7) or (8). Taken together, the relative and incremental value relevance results suggest that investors take investment properties revaluations into account when evaluating a real estate firm's market value of equity. These results are consistent with Muller, Riedl, and Sellhorn (2011) who find that fair value measurement compared to amortized cost measurement for investment properties mitigates information asymmetry. The results are also consistent with Liang and Riedl (2014) who provide anecdotal evidence that both EPS and NAV figures and their corresponding forecasts are primary inputs into analyst's target price estimates.

All value relevance regressions produce high adjusted R^2 above 94%. Although this seems high, Barth and Clinch (1998) also find adjusted R^2 of over 94% for a sample of Australian financial firms in the period between 1991 and 1995. The high R^2 may reflect the fact that, on average, more than 80% of the asset side of firms in our sample consists of investment properties measured in more than 90% at fair value. Nevertheless, we winsorize our sample at the 10^{th} and 90^{th} percentile to check whether the high R^2 is driven by outliers. Untabulated statistics show no reduction in R^2 from the procedure and no changes in the significance of the coefficients, except that *EPRA_EPS* becomes insignificant in model (5). In addition, we calculate studentized residuals from all regressions and repeat the regressions using only observations with absolute studentized residuals smaller than 2. Untabulated statistics show that the R^2 remains basically unchanged and that the significance level changes in model (5) where *EPRA_EPS* again becomes insignificant and in model (7) where *EPRA_EPS* - *EPS* becomes statistically significant (t-statistics of 2.26). However, *EPRA_EPS* - *EPS* becomes statistically insignificant again if we move the studentized residual threshold to 3, 2.5 or 1.5. Due to the sensitivity of the significance levels of *EPRA_EPS* - *EPS* to variations in studentized residual thresholds and due to the results in model (7)-(8), we conclude that we find no compelling evidence that EPRA EPS is value relevant.

3.6.2. Effects on Liquidity, Cost of Capital, and Analyst Following

We estimate the effects of EPRA BPR compliance on liquidity, cost of capital, and analyst following. We compute liquidity as the median logarithmic proportional weekly bid-ask spread measured three months after the reporting date (Log(*Spread*)). The spread is measured as the difference between the closing bid and ask price of the trading day divided by the midpoint. Following Hail and Leuz (2006), we estimate the ex-ante cost of capital implied in contemporaneous stock price and analyst forecast data according to four different models suggested in Claus and Thomas (2001), Gebhardt, Lee, and Swaminathan (2001), Ohlson and Juettner-Nauroth (2005), and Easton (2004). For some firm-quarters, estimates cannot be computed for all four models. The reason is that the underlying equation of the model does not always have an economically meaningful solution. To compensate the missing estimates, as well as to reduce a possible estimation bias, we compute the average value of the available cost of capital estimates. Cost of capital have—similar to the proportional bid-ask spread—a log-normal distribution. We therefore use the logarithm of the ex-ante cost of capital in our regressions (Log(*COC*)). We estimate the number of analysts following by counting the number of firm's annual earnings forecasts three months after the fiscal year end (*AnaCov*). We take earnings forecasts for the determination of analyst coverage because they are more frequent than NAV forecasts, which leads to more variation and eventually stronger inferences.

First, we analyze the effect of EPRA BPR compliance on liquidity by estimating the following regression:

$$\text{Log}(\mathit{Spread})_{i,t} = \beta_0 + \beta_1 \mathit{EPRA}_{i,t} + \beta_2 \mathit{Vol}_{i,t} + \beta_3 \mathit{Turnover}_{i,t} + \beta_4 \mathit{Size}_{i,t} + \beta_5 \mathit{Chs}_{i,t} + \beta_6 \mathit{LegalQuality}_{i,t} + \varepsilon_{i,t}\,, \tag{3.2}$$

where *EPRA* is one of three measures—*Medal*, *EPRA Overall Score*, or *EPRA Performance Measures*—described in Section 3.5.2. We consistently use year-fixed effects and robust standard errors clustered by firms. Following the current literature on the effects of disclosure on liquidity, we include stock volatility (*Vol*), share turnover (*Turnover*), and the logarithmic transformation of the market capitalization (*Size*) as control variables for effects unrelated to disclosure quality. In addition, we include inside ownership (*Chs*) into the regression because prior literature has shown that the association between disclosure quality and cost of capital can be separated into two separate effects: a direct effect in which disclosure reduces parameter uncertainty regarding the estimate of expected returns and an indirect effect in which disclosure reduces the need for inside ownership to align the entrepreneur and the reduced inside ownership increases cost of capital (Core, Hail, and Verdi, 2015). Core, Hail, and Verdi (2015) show that without controlling for inside ownership, the indirect effect abates the negative relation between disclosure quality and cost of capital. We also include legal quality (*LegalQuality*) because prior research has identified an association between disclosure quality and legal systems (e.g. Shleifer and Vishny, 1997; La Porta et al., 2000; and Leuz, Nanda, and Wysocki, 2003).

Table 3.7 reports the regression results of Equation (3.2). All three EPRA measures are significantly negative at the one-, five-, or ten-percent level for all model specifications. This indicates that firms compliant with the EPRA BPR show higher liquidity compared to firms that are not or only weakly compliant. The results further show that firms with low stock volatility, firms with high share turnover, larger firms, and firms with high proportions of closely held shares have higher liquidity, i.e., lower spreads. We, however, don't find any effects for the regulatory environment (*LegalQuality*). The regressions exhibit R^2 between 60% and 65% for the regression equation including control variable. This result is comparable to existing studies on the effects of disclosure on liquidity (e.g. Daske et al., 2013 and Christensen, Hail, and Leuz, 2013).

Second, we analyze the effect of EPRA BPR compliance on cost of capital by estimating the following regression:

$$\begin{aligned} \text{Log}(COC)_{i,t} = {} & \beta_0 + \beta_1 EPRA_{i,t} + \beta_2 Vol_{i,t} + \beta_3 Turnover_{i,t} + \beta_4 Size_{i,t} + \beta_5 Chs_{i,t} + \\ & \beta_6 LegalQuality_{i,t} + \beta_7 FcBias_{i,t} + \beta_8 Btm_{i,t} + \beta_9 Lev_{i,t} + \beta_{10} Roa_{i,t} + \varepsilon_{i,t} \qquad (3.3) \end{aligned}$$

We include all explanatory variables from Equation (3.2). Following Hail and Leuz (2006), we further control for forecast bias (*FcBias*), book-to-market ratio (*Btm*), leverage ratio (*Lev*), and return on assets (*Roa*).

Table 3.8 reports the regression results of Equation (3.3). The coefficients *Medal* and *EPRA Performance Measures* are significant either at the one- or five-percent level for all variants of the regression. The coefficients *EPRA Overall Score* is not significant in model (4), including control variables. The regressions exhibit R^2 between 30% and 35% for the full models, which is at the lower end of what Hail and Leuz (2006) find.[40] Further, the R^2 is considerably lower than what we get from Equation (3.2) and (3.4) using bid-ask spread and analyst coverage as outcome variables. We attribute this result to the fact that our proxy for the cost of capital is noisier than the other two outcome measures. The control variables exhibit signs that are in line with Hail and Leuz (2006) except for share turnover (*Turnover)*. The positive association between share turnover and cost of capital may stem from other underlying factors that are correlated with turnover such as the concurrent European debt crisis that might have struck firms with higher turnover more severely, increasing their cost of capital. We, however, gain confidence in our results from the fact that the omission of turnover does not change any signs or the significance of the main coefficients. Overall, the results show that EPRA BPR compliant firms have lower cost of capital.

Third, we analyze the effect of EPRA BPR compliance on analyst following by estimating the following regression:

$$AnaCov_{i,t} = \beta_0 + \beta_1 EPRA_{i,t} + \beta_2 Vol_{i,t} + \beta_3 Turnover_{i,t} + \beta_4 Size_{i,t} + \beta_5 Chs_{i,t} + \beta_6 LegalQuality_{i,t} + \beta_7 FcBias_{i,t} + \beta_8 Btm_{i,t} + \beta_9 Lev_{i,t} + \beta_{10} Roa_{i,t} + \varepsilon_{i,t} \qquad (3.4)$$

Table 3.9 reports the regression results of Equation (3.4). All three EPRA measures are significantly positive at the one- or five-percent level. This indicates that firms that comply to a greater extent with EPRA BPR have greater analyst coverage.

A central issue related to the results in Table 3.7, 3.8, and 3.9 is that some firms already complied to a certain extent with EPRA BPR in the first year of our sample period in 2009 whereas other firms have never started complying to any extent with EPRA BPR until the end of the sample period in 2013. That means that the association between capital market

[40] Hail and Leuz (2006) have an R^2 between 36% and 60% for the regressions of the cost of capital measures. Compared to their study, we use the logarithmic transformation of the cost of capital, which reduces our R^2 by up to 90bp.

outcomes and the degree of compliance with EPRA BPR should not be interpreted that changes in the degree of compliance are associated with positive changes in market outcomes but rather that firms with greater compliance show better market outcome characteristics. This finding may very well be driven by other underlying factors such as better skilled managers may generate good capital market outcomes through their activities and efforts, which they would like to make visible to investors through increased disclosure. Alternatively, larger firms have been shown to be associated with better capital market outcomes. At the same time, larger firms have greater resources for reporting purposes, which they may use to disclose additional information to investors.

To tackle this issue, we proceed with our analysis by restricting our sample to firms that have become compliant to EPRA BPR during the sample period, i.e., firms for which we have observations before and after EPRA BPR adoption. This procedure leads to 29 remaining firms with 145 firm-year observations. Due to the limited sample size, we try to identify a variable for EPRA BPR compliance that best distinguishes between serious adoption and non-adoption. We conduct a one-way analysis of variance (ANOVA) on our full sample suggesting that Log(*Spread*), Log(*COC*), and *AnaCov* are not equal among gold, silver, and bronze medals. Post-hoc pairwise comparison based upon the studentized range distribution using the modified least significant difference test by Fisher (1935) and Hayter (1986) further indicates that Log(*Spread*), Log(*COC*), and *AnaCov* are significantly different between gold and bronze and between silver and bronze but not between gold and silver at the five-percent level.[41] As a consequence, we construct an dichotomous variable (*EPRA Application*) equal to one in each year that firms received either a silver or gold medal in the EPRA Annual Report Survey and zero otherwise.

[41] The result that silver and gold is viewed as a serious commitment to disclosure whereas bronze is not, is underlined by remarks in Deloitte and EPRA (2015) saying that firms receive bronze accreditation by disclosing only three EPRA metrics. However, to receive gold accreditation firms need to disclose, amongst others, all six EPRA metrics, detailed information on investment assets, an EPRA performance measure summary table, and an analysis of like-for-like rental income growth (Deloitte and EPRA, 2014).

Again, we regress Log(*Spread*), Log(*COC*), and *AnaCov* on *EPRA Application*, control variables, and year-fixed effects.

Table 3.10 outlines the regression results suggesting that firms that became EPRA-BPR-compliant benefit from an increase in liquidity and an increase in analyst coverage. For the firms' cost of capital we fail to observe a significant effect of EPRA application, which may be attributable to the underlying noise of our costs-of-capital proxy. Further, we see that overall disclosure (*Notes_Pages*)—using the number of pages of the financial statement notes—is significantly negative associated with Log(*Spread*). In addition, the association between *EPRA Application* and Log(*Spread*) and between *EPRA Application* and *AnaCov*, respectively, is unaffected by the inclusion of the overall disclosure proxy. Untabulated statistics show that Pearson's correlation between overall disclosure and EPRA application is close to zero (-0.0257). Hence it is unlikely that the two measures are proxies that capture essentially the same underlying economics. [42]

We further conjecture that if EPRA BPR compliance leads to positive capital market outcomes, we should also be able to detect negative capital market effects if firms switch back from EPRA compliance to non-compliance. Thus, we restrict our overall sample to 12 firms with 60 firm-year observations that switched back from compliance to non-compliance during the sample period. We regress Log(*Spread*), Log(*COC*), and *AnaCov* on *SwitchBack*, *Non_adoption*, control variables that might be correlated with the de-adoption of EPRA BPR and might influence capital market outcomes, and year-fixed effects. We include *Non_adoption* in order for *SwitchBack* to reflects the difference in capital market outcomes between firm-years after a switch back from compliance to non-compliance for as long as

[42] We repeat all three regressions substituting *EPRA Application* by *Medal*. The regression results look very similar where the main variable *Medal* is negatively related to Log(*Spread*), not related to Log(*COC*), and positively related to *AnaCov*. The signs of the control variables all remain the same but *Notes_Pages* becomes insignificant in model (1) and Log(*Returns*) becomes significantly negative in model (2).

they remain non-compliant and firm-years in which firms comply with EPRA BPR to an extent such that they receive at least a silver medal.

Table 3.11 shows evidence that firms switching back from compliance to non-compliance indeed exhibit negative capital market outcomes. In addition, results show that *Non_adoption* tends to be associated with negative capital market outcomes relative to adopters, which is what we expect.

Overall, our findings provide evidence indicating that positive capital market effects are associated with higher levels of EPRA disclosure. Moreover, the results also show that changes in the level of EPRA disclosure are associated with changes in capital market outcomes. It is, however, crucial to emphasize that our research design and our setting does not allow for causal inferences. For example, we are unable to identify whether an increase in the degree of compliance with EPRA BPR attracts more analysts or whether an increase in the number of analysts following increases the demand for EPRA BPR. Nevertheless, the association between analyst following and the degree of EPRA BPR compliance suggests that analysts deem EPRA information useful.

3.6.3. Factors of EPRA BPR Compliance

We proceed to investigate the managerial incentives to comply with EPRA BPR. To shed light on the determinants of EPRA adoption and the degree of compliance with EPRA, we estimate two equations. First, we run probit regressions of the following form:

$$\begin{aligned} \mathit{EPRA\ Following}_{i,t} = {} & \beta_0 + \beta_1 \mathit{Size}_{i,t} + \beta_2 \mathit{Btm}_{i,t} + \beta_3 \mathit{Vol}_{i,t} + \beta_4 \mathit{Log(Returns)}_{i,t} + \\ & \beta_5 \mathit{DebtOffering}_{i,t} + \beta_6 \mathit{SeasonedEquityOffering}_{i,t} + \\ & \beta_7 \mathit{LegalQuality}_{i,t} + \beta_8 \mathit{Number\_of\_EPRA\_adopters}_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{3.5}$$

where *EPRA Following* is either *EPRA Adoption*, an indicator variable equal to one when firms received their first silver or gold medal in the EPRA Annual Report Survey for the time period between 2010 and 2013 and zero otherwise, or *EPRA Application*, an indicator variable equal to one if firms received either a gold or silver medal in the EPRA Annual Report Survey in the time period between 2009 and 2013 and zero otherwise.

Second, we run OLS regressions of the following form:

$$\begin{aligned} EPRA\ Compliance_{i,t} = {} & \beta_0 + \beta_1 Size_{i,t} + \beta_2 Btm_{i,t} + \beta_3 Vol_{i,t} + \beta_4 Log(Returns)_{i,t} + \\ & \beta_5 DebtOffering_{i,t} + \beta_6 SeasonedEquityOffering_{i,t} + \\ & \beta_7 LegalQuality_{i,t} + \beta_8 Number\_of\_EPRA\_adopters_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{3.6}$$

where *EPRA Compliance* is either *EPRA Overall* Score or *EPRA Performance Measures*, as described in Section 3.5.2.

Table 3.12 presents the regression results of Equation (3.5) and (3.6). We conjecture that managers may be willing to disclose additional information if they intend to issue debt or equity to the market in order to increase transparency, and thus lower their refinancing costs. Model (1) reports positive and significant coefficient estimates for *DebtOffering* demonstrating that issuance of debt is positively associated with EPRA BPR adoption. More specifically, firms that issue debt within one year after the financial year end are more likely to adopt EPRA BPR to the extent of at least receiving a silver medal in the EPRA Annual Report Survey.

Acknowledging that some of the other effects may not be borne out because we only have 29 firms that newly adopt EPRA BPR in the time window between 2010 and 2013, we also investigate the association between EPRA application and the same potential determinants as in model (2). The positive association of debt offerings remains significant. Most interestingly, the marginal effect of a debt offering increases to 12.9%, which speaks to the importance of incorporating EPRA BPR in the annual reports if a firm needs debt capital.

Next we investigate the role of those determinants on the degree of compliance with EPRA BPR where we replace the dichotomous variable *EPRA Following* by continuous variables for *EPRA Compliance*, i.e., *EPRA Overall Score* and *EPRA Performance Measures*. Again, the coefficients on debt offering remain significant. Interestingly, the logarithmic transformation of the annual stock price return (*Log(Returns)*) becomes significantly negatively associated with the degree of compliance, i.e., firms with lower annual stock price performance exhibit higher compliance with EPRA BPR. This result seems to stand in contrast to the notion that managers choose to opaque their performance during times with low stock price performance (Lang and Lundholm, 1996). However, as stock price performance can hardly be hidden from investors, managers may be more willing to provide additional disclosure to explain poor performance (Leuz and Wysocki, 2016).

3.7. Conclusion

This study provides evidence that voluntary application of standardized industry-specific accounting guidance beyond IFRS provides information relevant to investors. We exploit the listed European real estate setting to examine the usefulness, the economic effects, and the determinants of EPRA BPR disclosures. We start by investigating whether EPRA NAV, EPRA NNNAV, and EPRA EPS are value relevant, i.e., whether investors deem the information useful. We proceed to examine whether EPRA BPR compliance induces positive economic effects such as higher liquidity, lower cost of capital, and more analysts following. Lastly, we analyze which factors increase the likelihood of adopting EPRA BPR and which factors determine the extent to which firms comply with EPRA BPR.

First, we find that EPRA NAV and EPRA NNNAV are relatively and incrementally value relevant. Second, we show that firms, complying with EPRA BPR exhibit lower cost of capital, higher stock liquidity, and higher analyst following. A central issue, however, is that some firms already complied to a certain extent with EPRA BPR in the first year of our sample period in 2009 whereas other firms have never started complying to any extent with EPRA BPR until the end of the sample period in 2013. To tackle this issue, we proceed with our analysis by restricting our sample to firms for which we have observations before and after EPRA BPR adoption. The regression results suggest that firms that became EPRA-BPR-compliant benefit from an increase in liquidity and an increase in analyst coverage. For the firms' cost of capital we fail to observe a significant effect from EPRA application. In addition, further analyses provide evidence that firms switching back from compliance to non-compliance exhibit negative capital market outcomes. Third, we find that firms' debt offering plans play an important role for the firms' decision to comply with EPRA BPR.

It is crucial to emphasize that our research design and our setting does not allow for causal inferences. For example, we are unable to identify whether an increase in the degree of compliance with EPRA BPR attracts more analysts or whether an increase in the number of analysts following increases the demand for EPRA BPR. In addition, the association of cross-sectional variation in firm's *choice* in disclosure levels under the existing environment does not need to generalize to the effects of *regulation* on capital market outcomes. Put differently, the insides we gather from this study in the European real estate environment cannot be used to justify the desirability or need for mandated disclosure. The reason is that precisely in the European real estate industry where benefits of disclosure mostly exceed their costs; we do not need regulation (Leuz and Wysocki, 2016).

References

Armstrong, C.S., Barth, M.E., Jagolinzer, A.D., and Riedl, E.J. 2010. Market reaction to the adoption of IFRS in Europe. *The Accounting Review* (85): 31–61.

Baiman, S. and Verrecchia, R.E. 1996. The relation among capital markets, financial disclosure, production efficiency, and insider trading. *Journal of Accounting Research* (34): 1–22.

Barth, M.E., Beaver, W.H., and Landsman W.R. 2001. The relevance of the value relevance literature for financial accounting standard setting: Another view. *Journal of Accounting and Economics* (31): 77–104.

Barth, M.E. and Clinch, G. 1998. Revalued financial, tangible, and intangible assets: Associations with share prices and non-market-based value estimates. *Journal of Accounting Research* (36): 199–233.

Balakrishnan, K., Billings, M.B., Kelly, B., and Ljungqvist, A. 2014. Shaping liquidity: On the causal effects of voluntary disclosure. *Journal of Finance* (69): 2237–2278.

Bhushan, R. 1989. Firm characteristics and analyst following. *Journal of Accounting and Economics* (11): 255-274.

Botosan, C.A. 1997. Disclosure level and the cost of equity capital. *The Accounting Review* (72): 323–349.

Byard, D., Li, Y., and Yu, Y. 2011. The effect of mandatory IFRS adoption on financial analyst's information environment. *Journal of Accounting Research* (49): 69–96.

Charoenwong, C., Chong, B.S., and Yang, Y.C. 2014. Asset liquidity and stock liquidity: International evidence. *Journal of Business Finance and Accounting* (41): 435–468.

Christensen, H.B., Hail, L., and Leuz, C. 2013. Mandatory IFRS reporting and changes in enforcement. *Journal of Accounting and Economics* (56): 147–177.

Claus, J. and Thomas, J. 2001. Equity premia as low as three percent? Evidence from analysts' earnings forecasts for domestic and international stock markets. *Journal of Finance* (56): 1629–1666.

Core, J.E., Hail, L., and Verdi, R.S. 2015. Mandatory disclosure quality, inside ownership, and cost of capital. *European Accounting Review* (24): 1–29.

Cuijpers, R. and Buijink, W. 2005. Voluntary adoption of non-local GAAP in the European Union: A Study of determinants and consequences. *European Accounting Review* (14): 487–524.

Daske, H. 2006. Economic benefits of adopting IFRS or US-GAAP – Have the expected cost of equity capital really decreased? *Journal of Business Finance and Accounting* (33): 329–373.

Daske, H., Hail, L., Leuz, C., and Verdi, R. 2008. Mandatory IFRS reporting around the world: Early evidence on the economic consequences. *Journal of Accounting Research* (46): 1085–1142.

Daske, H., Hail, L., Leuz, C., and Verdi, R. 2013. Adopting a label: Heterogeneity in the economic consequences around IAS/IFRS adoptions. *Journal of Accounting Research* (50): 495–547.

DeFond, M., Hu, X., Hung, M., and Li, S. 2011. The impact of mandatory IFRS adoption on foreign mutual fund ownership: The role of comparability. *Journal of Accounting and Economics* (51): 240–258.

Deloitte and European Public Real Estate Association (EPRA). 2014. *Speeding ahead – EPRA Annual Report Survey 2013/14*. https://www2.deloitte.com/content/dam/Deloitte/lt/Documents/real-estate/LT_epra_en.pdf.

Deloitte and European Public Real Estate Association (EPRA). 2015*. Gaining momentum – EPRA Annual Report Survey 2014/15*. https://www2.deloitte.com/content/dam/Deloitte/be/ Documents/realestate/be_fas_real-estate_epra_annual_report_2014-2015.pdf.

Dhaliwal, D.S., Li, O.Z., Tsan, A., and Yang, Y.G. 2011. Voluntary nonfinancial disclosure and the cost of equity capital: The initiation of corporate social responsibility reporting. *The Accounting Review* (86): 59–100.

Diamond, D. and Verrecchia, R.E. 1991. Disclosure, liquidity and the cost of capital. *Journal of Finance* (46): 1325–59.

Easton, P.D. 2004. PE ratios, PEG ratios, and estimating the implied expected rate of return on equity capital. *The Accounting Review* (79): 73–95.

Easton, P.D., Eddey, P.H., and Harris, T.S. 1993. An investigation of revaluations of tangible long-lived assets. *Journal of Accounting Research* (31): 1–38.

European Public Real Estate Association (EPRA). 2010. *Best Practice Recommendations*. Retrieved from http://www.epra.com/media/EPRA_2010_BPR.pdf.

European Public Real Estate Association (EPRA). 2014. *Best Practice Recommendations*. Retrieved from http://www.epra.com/media/EPRA_Best_Practices_Recommendations_BPR_-_Dec2014_1436191395537.pdf.

European Public Real Estate Association (EPRA). 2015. *FTSE EPRA/NAREIT Global Real Estate Index Series v. 6.7*. Retrieved from http://www.epra.com/media/FTSE_EPRA_NAREIT_Global_Real_Estate_Index_Series_v6_1453454619715.7.pdf.

Fisher, R.A. 1935. *Design of Experiments*. London: Oliver & Boyd.

Francis, J., Nanda, D., and Olsson, P. 2008. Voluntary disclosure, earnings quality, and cost of capital. *Journal of Accounting Research* (46): 53–99.

Gao, F., Dong, Y., Ni, C., and Fu, R. 2016. Determinants and economic consequences of non-financial disclosure quality. *European Accounting Review* (25): 287–317.

Gebhardt, W.R., Lee, C.M., and Swaminathan, B. 2001. Toward an implied cost of capital. *Journal of Accounting Research* (39): 135–176.

Goh, B., Li, D., Ng, J., and Yong, K. 2015. Market pricing of banks' fair value assets reported under SFAS 157 since the 2008 financial crisis. *Journal of Accounting and Public Policy* (34): 129–145.

Guay, W., Samuels, D., and Taylor, D. 2016. Guiding through the fog: Financial statement complexity and voluntary disclosure. *Journal of Accounting and Economics* (62): 234–269.

Hail, L. 2002. The impact of voluntary corporate disclosure on the ex-ante cost of capital for Swiss firms. *European Accounting Review* (11): 741–773.

Hail, L. and Leuz, C. 2006. International differences in the cost of capital: Do legal institutions and securities regulation matter? *Journal of Accounting Research* (44): 485–531.

Hayter, A.J. 1986. The maximum familywise error rate of Fisher's least significant difference test. *Journal of the American Statistical Association* (81): 1001-1004.

Healy, P.M., Hutton, A.P., and Palepu, K.G. 1999. Stock performance and intermediation changes surrounding sustained increases in disclosure. *Contemporary Accounting Research* (16): 485–520.

Healy, P.M. and Palepu, K.G. 2001. Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *Journal of Accounting and Economics* (31): 405–440.

Healy, P.M., Palepu, K.G., and Sweeney, A.P. 1995. Causes and consequences of expanded voluntary disclosure. *Working Paper, MIT Sloan School of Management*.

Horton, J., Serafeim, G., and Serafeim, I. 2013. Does mandatory IFRS adoption improve the information environment? *Contemporary Accounting Research* (30): 423–436.

Kaufmann, D., Kraay, A., and Mastruzzi, M. 2010. The worldwide governance indicators: Methodology and analytical issues. *World Bank Policy Research Working Paper No. 5430*.

Khurana, I.K. and Michas, P.N. 2011. Mandatory IFRS adoption and the U.S. home bias. *Accounting Horizons* (25): 729–753.

Kim, O. and Verrecchia, R.E. 1994. Market liquidity and volume around earnings announcements. *Journal of Accounting and Economic* (17): 41–67.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., and Vishny, R. 2000. Investor protection and corporate governance. *Journal of Financial Economics* (58): 3–27.

Landsman, W.R., Peasnell, K.V., and Shakespeare, C. 2008. Are asset securitizations sales or loans? *The Accounting Review* (83): 1251–1272.

Lang, M.H. and Lundholm, R.J. 1993. Cross-sectional determinants of analyst ratings of corporate disclosures. *Journal of Accounting Research* (31): 246–271.

Lang, M.H. and Lundholm, R.J. 1996. Corporate disclosure policy and analyst behavior. *The Accounting Review* (71): 467–492.

Lang, M.H. and Stice-Lawrence, L. 2015. Textual analysis and international financial reporting: Large sample evidence. *Journal of Accounting and Economics* (60): 110–135.

Leuz, C. 2003. IAS versus U.S. GAAP: Information asymmetry-based evidence from Germany's new market. *Journal of Accounting Research* (41): 445–472.

Leuz, C., Nanda, D., and Wysocki, P.D. 2003. Earnings management and investor protection: An international comparison. *Journal of Financial Economics* (69): 505– 527.

Leuz, C. and Verrecchia, R.E. 2000. The economic consequences of increased disclosure. *Journal of Accounting Research* (38): 91–124.

Leuz, C. and Wysocki, P.D. 2016. The economics of disclosure and financial reporting regulation: Evidence and suggestions for future research. *Journal of Accounting Research* (54): 525–622.

Levene, H. 1960. Robust tests for equality of variances, in: *Contributions to Probability and Statistics: Essays in Honor of Harold Hotelling*, ed. Olkin, I., Ghurye, S.G., Hoeffding, W., Madow, W.G., and Mann, H.B, 278–292. Menlo Park, CA: Stanford University Press.

Li, S. 2010. Does mandatory adoption of International Financial Reporting Standards in the European Union reduce the cost of equity capital? *The Accounting Review* (85): 607–636.

Liang, L. and Riedl, E.J. 2014. The effect of fair value versus historical cost reporting model on analyst forecast accuracy. *The Accounting Review* (89): 1151–1177.

Muller, K.A., Riedl, E.J., and Sellhorn, T. 2011. Mandatory fair value accounting and information asymmetry: Evidence from the European real estate industry. *Management Science* (57): 1138–1153.

Ohlson, J.A. and Juettner-Nauroth B.E. 2005. Expected EPS and EPS growth as determinants of value. *Review of Accounting Studies* (10): 349–365.

Schoenfeld, J. 2017. The effect of voluntary disclosure on stock liquidity: New evidence from index funds. *Journal of Accounting and Economics* (63): 51–74.

Sengupta, P. 1998. Corporate disclosure quality and the cost of debt. *The Accounting Review* (73): 459–474.

Shima, K.M. and Gordon, E.A. 2011. IFRS and the regulatory environment: The case of U.S. investor allocation choice. *Journal of Accounting and Public Policy* (30): 481–500.

Shleifer, A. and Vishny, R. 1997. A survey of corporate governance. *Journal of Finance* (52): 737–783.

Welker, M. 1995. Disclosure policy, information asymmetry, and liquidity in equity markets. *Contemporary Accounting Research* (11): 801–827.

Zhang, G. 2001. Private information production, public disclosure, and the cost of capital: Theory and implication. *Contemporary Accounting Research* (18): 363–384.

Tables

Table 3.1: Sample Selection

	Change	Remaining
Constituent of FTSE EPRA/NAREIT Developed Europe Index as of November 19, 2014		95
Real estate firms that are EPRA Members as of December 20, 2014	+26	121
Less firms		
not publicly listed	0	121
not reporting under IFRS	0	121
for which no annual reports were found	-9	112
Potential firm-year observations (112 firms times 5 fiscal years)		560
Less firm-years:		
in which firm is not publicly traded (e.g. inexistent, merged, bankrupt)	-32	528

This table presents the sample selection process. We begin with all firms that are constituents of the FTSE EPRA/NAREIT Developed Europe index as of November 19, 2014 (95). We additionally include real estate firms that are members of the EPRA as of December 20, 2014 (+26). Our base sample comprises of 121 investment property firms, of which all firms apply IFRS and are publicly traded. We exclude firms for which annual reports are unavailable (-9). This leaves 112 potential sample firms. Our sample period spans five fiscal years starting in 2009 when the EPRA Best Practice Recommendations were revised extensively up to 2013. This leads to 560 potential firm-year observations (112 firms times 5 fiscal years). We eliminate firm-years, in which firms are no publicly traded (-32), which might be the case because firms where inexistent at that time, merged with another company, or ceased their existence. Eventually, we are left with a sample that comprise of 528 firm-years. The firm-year observations are distributed over time as follows: 97 (2009); 103 (2010); 108 (2011); 110 (2012); and 110 (2013).

Table 3.2: Disclosure Statistics

Variable	N	Mean	Std. dev.	Min	p25	Median	p75	Max	Score
Annual reports statistics									
Number of pages	525	155.84	91.89	29.00	100.00	137.00	184.00	704.00	
Number of pages for notes	521	40.56	23.34	0.00	24.00	35.00	52.00	160.00	
EPRA count	527	23.97	32.84	0.00	1.00	12.00	33.00	199.00	
Number of EPRA figures	528	3.36	3.48	0.00	0.00	2.00	6.00	11.00	
Separate EPRA Part	526	0.20	0.40	0.00	0.00	0.00	0.00	1.00	1/24
External valuation for IP	484	0.90	0.30	0.00	1.00	1.00	1.00	1.00	1/24
Frequency of IP valuations (# per year)	459	1.25	0.74	0.00	1.00	1.00	1.00	4.00	
Lists major properties	528	0.66	0.47	0.00	0.00	1.00	1.00	1.00	1/24
Lists of (re-)development properties	526	0.25	0.44	0.00	0.00	0.00	1.00	1.00	1/24
Number of EPRA tables	528	0.25	0.91	0.00	0.00	0.00	0.00	5.00	5/24
English version available	528	0.97	0.17	0.00	1.00	1.00	1.00	1.00	1/24
Investment property measurement (in mio. EUR except stated otherwise)									
Valuation at fair value (1 or 0)	526	0.92	0.26	0.00	1.00	1.00	1.00	1.00	1/24
Fair value	490	2,464.05	3,472.92	2.84	594.96	1,266.23	2,767.50	28,852.60	
Fair value in notes	43	4,309.95	4,494.60	307.94	688.74	2,566.60	6,260.80	15,738.64	
Historical costs	38	3,621.04	3,404.18	115.83	1,423.46	2,460.94	4,820.40	11,301.04	
Fair value adjustments	483	34.68	197.77	-2,192.10	-9.60	6.61	53.00	1,702.30	
Adjustment on highest and best use	26	2.96	8.13	0.00	0.00	0.00	0.00	35.19	1/24
EPRA Performance Measures (in mio. EUR (earnings, NAV, NNAV) and percent)									
EPRA earnings	187	84.06	150.06	-739.00	17.53	36.61	103.51	985.80	2/24
EPRA NAV	261	1,848.91	2,458.53	1.30	395.84	786.31	2,273.84	15,477.00	2/24
EPRA NNAV	190	2,300.21	2,651.07	1.16	401.33	1,336.96	3,148.21	14,640.00	2/24
EPRA net initial yield	113	5.77	1.12	0.51	5.20	5.74	6.30	8.30	1/24
EPRA net initial yield topped up	94	5.83	0.91	2.10	5.30	5.80	6.40	7.70	1/24
EPRA vacancy rate	175	7.31	5.97	0.40	3.40	5.70	10.00	41.40	2/24
EPRA cost ratio incl. direct vacancy costs	29	18.93	5.95	0.33	17.24	20.30	22.90	28.98	1/24
EPRA cost ratio excl. direct vacancy costs	28	17.74	5.48	2.60	15.19	18.35	20.85	28.29	1/24

The global sample comprises of 528 firm-year observations from 112 real estate firms in 16 countries between 2009 and 2013. All data provided in this table are hand-collected from annual reports. The *Number of pages* corresponds to the total number of pages of the annual report. *Number of pages for notes* is the number of the pages of the financial group statement's notes. *EPRA count* is the count of the word "EPRA" in the annual report. *Number of EPRA figures* is the number of EPRA performance measures disclosed. *Separate EPRA Part* is an indicator variable equal to one if the annual report has a separate part for their EPRA information and zero otherwise. *External valuation for IP* is an indicator equal to one if their investment properties are based on the assessment of external appraisers and zero otherwise. *Frequency of IP valuations* counts how many times the external appraisers assess the value of the investment properties per financial year. *Lists major property* is an indicator variable equal to one if the annual report includes a list of their ten-most-valuable properties and zero otherwise. *Lists of (re-)development properties* is an indicator variable equal to one if the annual report includes a list of all development and redevelopment properties. *Number of EPRA tables* is the number of EPRA-specified tables in the annual report. *English version available* is an indicator variable equal to one if the annual report is publicly available in English language. *Valuation at fair value* is an indicator variable equal to one if investment properties are recognized at fair value. *Fair value* is the fair value amount of all investment properties measured at fair value. *Fair value in the notes* is the disclosed fair value amount of all investment properties recognized at historical cost. *Historical cost* is the historical cost amount of all investment properties measured at historical cost. *Fair value adjustments* is the total fair value change in investment properties during a financial year. *Adjustment on highest and best use* is the change in investment properties that is due to the new fair value definition (highest and best use) in IFRS 13, which is to be applied for annual periods beginning on or after 1 January 2013. *EPRA Performance measures* is the amount that is disclosed in the annual report for each of the eight performance figures. The last column "Score" defines how the *EPRA overall score* was constructed and defines their respective weights.

Table 3.3: Spearman and Pearson Correlations

Variables	Log(Spread)	Log(COC)	AnaCov	Turnover	FcBias	Medal	EPRA Overall Score	EPRA Performance Measures	EPRA Application	Gold	Silver	Bronze	Separate EPRA Part
Market Outcomes													
Log(Spread)		0.339 ***	-0.627 ***	-0.613 ***	0.110 **	-0.425 ***	-0.362 ***	-0.336 ***	-0.421 ***	-0.355 ***	-0.193 ***	-0.081 *	-0.172 ***
Log(COC)	0.305 ***		-0.244 ***	0.030	0.046	-0.211 ***	-0.169 ***	-0.198 ***	-0.255 ***	-0.203 ***	-0.128 ***	0.028	-0.101
AnaCov	-0.620 ***	-0.2397 ***		0.428 ***	-0.045	0.476 ***	0.279 ***	0.322 ***	0.4541 ***	0.3752 ***	0.2171 ***	0.115 ***	0.1245 ***
Turnover	-0.3073 ***	0.3122 ***	0.238 ***		-0.031	0.299 ***	0.234 ***	0.183 ***	0.282 ***	0.207 ***	0.166 ***	0.076 *	0.070
FcBias	0.1128 **	0.0174	-0.113 **	0.008		0.006	0.039	0.051	-0.072	-0.075 *	-0.015	0.112 **	-0.043
Disclosure Proxies													
Medal	-0.4331 ***	-0.1982 ***	0.500 ***	0.103 **	-0.027		0.595 ***	0.624 ***	0.7906 ***	0.5816 ***	0.464 ***	0.475 ***	0.456 ***
EPRA Overall Score	-0.3453 ***	-0.1317 ***	0.285 ***	0.032	-0.018	0.628 ***		0.940 ***	0.5631 ***	0.4923 ***	0.237 ***	0.150 ***	0.618 ***
EPRA Performance Measures	-0.3525 ***	-0.1939 ***	0.334 ***	-0.013	-0.030	0.657 ***	0.941 ***		0.580 ***	0.512 ***	0.238 ***	0.172 ***	0.608 ***
EPRA Application	-0.432 ***	-0.2251 ***	0.492 ***	0.102 **	-0.107 **	0.791 ***	0.640 ***	0.643 ***		0.736 ***	0.587 ***	-0.163 ***	0.531 ***
Gold	-0.3663 ***	-0.1729 ***	0.413 ***	0.080 *	-0.075 *	0.582 ***	0.598 ***	0.597 ***	-0.169 ***		-0.117 ***	-0.120 ***	0.425 ***
Silver	-0.1954 ***	-0.1204 **	0.228 ***	0.053	-0.067	0.464 ***	0.224 ***	0.229 ***	0.587 ***	-0.117 ***		-0.096 **	0.271 ***
Bronze	-0.0769 *	0.0067	0.098 **	0.020	0.109 **	0.475 ***	0.092 **	0.135 ***	-0.163 ***	-0.120 ***	-0.096 ***		-0.027
Separate EPRA Part	-0.1749 ***	-0.0655	0.126 ***	-0.011	-0.064	0.456 ***	0.718 ***	0.676 ***	0.531 ***	0.425 ***	0.271 ***	-0.027	

This table reports pairwise Spearman's rank correlation coefficients in the upper right corner and Pearson's product-moment correlation in the lower left corner. *Log(Spread)* is the logarithmic transformation of the weekly median quoted bid-ask spread (i.e., difference between the bid and ask price divided by the midpoint and measured at the end of each trading day) measured four month after the financial year end. Following Hail and Leuz (2006), *Log(COC)* is the logarithmic transformation of the mean cost of capital calculated in accordance with four different model specifications suggested in (1) Claus and Thomas (2001), (2) Gebhardt, Lee and Swaminathan (2001), (3) Ohlson and Juettner-Nauroth (2005), and (4) Easton (2004). *AnaCov* is the number of analysts following a firm three months after the financial year end. *Turnover* is the yearly turnover volume in the financial year divided by the average number of common shares outstanding. *FcBias* is the difference between the mean financial year end earnings forecast eleven month before the financial year end and the actual earnings as stated in the financial statements. *Medal* is an indicator variable equal to one if firm's annual statement was awarded any medal in the Annual Report Survey conducted by Deloitte and zero otherwise. *EPRA Overall Score* is a self-constructed measure to proxy for the extent to which firms comply with EPRA BPR. *EPRA Performance Measures* is the number of disclosed EPRA performance measures in an annual report. *EPRA Application* is an indicator variable equal to one in each year firms received either a silver or gold medal in Deloitte's EPRA Annual Report Survey and zero otherwise. *Gold* is an indicator variable equal to one if firm's annual statement was awarded a gold medal in the Annual Report Survey conducted by Deloitte and zero otherwise. *Silver* is an indicator variable equal to one if firm's annual statement was awarded a silver medal in the Annual Report Survey conducted by Deloitte and zero otherwise. *Bronze* is an indicator variable equal to one if firm's annual statement was awarded a bronze medal in the Annual Report Survey conducted by Deloitte and zero otherwise. *Separate EPRA Part* is an indicator variable equal to one if the annual report has a separate part for their EPRA information and zero otherwise. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels,

Table 3.4: Summary Statistics

Variable	N	Mean	Std. dev.	Min	p25	Median	p75	Max
Disclosure measurement								
Medal	528	0.30	0.46	0	0	0	1	1
Gold	528	0.13	0.33	0	0	0	0	1
Silver	528	0.08	0.28	0	0	0	0	1
Bronze	528	0.09	0.28	0	0	0	0	1
EPRA Overall Score	528	0.38	0.21	0.08	0.25	0.33	0.52	1
EPRA Performance Measures	528	0.65	0.48	0	0	1	1	1
EPRA Adoption	418	0.06	0.23	0	0	0	0	1
EPRA Application	528	0.21	0.41	0	0	0	0	1
SwitchBack	52	0.48	0.50	0	0	0	1	1
Mechanisms								
Log(*Spread*)	521	-5.37	1.15	-8.15	-6.14	-5.36	-4.62	-1.25
Log(*COC*)	460	-2.57	0.48	-3.83	-2.83	-2.60	-2.37	-0.43
AnaCov	528	6.41	5.60	0	2	4	10	23
Value Relevance								
PPS	111	0	0.01	0	0	0	0	0.04
BVE_PS	111	0.04	0.05	0	0	0.01	0.06	0.23
EPRA_NAV_PS	111	0.04	0.06	0	0	0.01	0.05	0.36
EPRA_NNNAV_PS	111	0.04	0.05	0	0	0.01	0.05	0.31
EPS	111	0.13	0.22	0	0.02	0.05	0.15	1.45
EPRA_EPS	111	3.33	18.73	0	0.02	0.09	0.36	128.11
Liquidity controls								
Vol	521	0.04	0.02	0.01	0.02	0.04	0.05	0.3
Turnover	516	0.43	0.59	0	0.10	0.33	0.53	5.53
Size	521	6.45	1.24	2.51	5.65	6.46	7.24	10.21
Chs	528	0.48	0.50	0	0	0	1	1
LegalQuality	528	1.49	0.35	0.30	1.30	1.59	1.74	1.91
Additional controls								
FcBias	513	1.57	9.71	-25.27	-0.14	0.02	0.62	148.25
Btm	520	1.27	0.64	0	0.91	1.12	1.50	5.03
Lev	517	0.53	0.17	0.01	0.44	0.55	0.65	0.95
Roa	522	4.62	5.10	-14.82	2.22	4.27	6.35	39.23
Others								
Log(Returns)	513	0.09	0.29	-1.16	-0.04	0.09	0.25	1.1
Number_of_EPRA_adopters	528	69.44	17.43	39	59	74	85	86
SeasonedEquityOffering	394	0.40	0.49	0	0	0	1	1
DebtOffering	261	0.38	0.49	0	0	0	1	1

This table reports summary statistics of the variables used in our regression models. We report number of observations (*N*), mean (Mean), standard deviation (Std. dev.), minimum (Min), 25th percentile (p25), 50th percentile (Median), 75th percentile (p75), and maximum (Max). For the definitions of the variables refer to Appendix 3.A.

Table 3.5: Sample Distribution

Panel A: Distributional statistics for the measurement and disclosure scores by country

		Measurement				Medals			
Country	Total observations	# Firm-years measuring IP at FV	# Firm-years measuring IP at AC	# Avg Number of EPRA Figures	Avg EPRA Overall Score	Gold	Silver	Bronze	Total
Austria	20	20	0	2.55	0.3326	0	1	1	2
Belgium	39	39	0	5.26	0.5477	13	2	1	16
Finland	15	15	0	6.33	0.5045	6	3	2	11
France	53	43	10	4.26	0.4250	8	12	4	24
Germany	67	52	15	2.33	0.2772	4	2	5	11
Greece	14	14	0	0	0.1369	0	0	0	0
Israel	9	9	0	4.11	0.3628	0	0	0	0
Italy	10	10	0	0.7	0.2818	0	0	2	2
Luxembourg	15	15	0	1.87	0.3293	0	0	0	0
Netherlands	25	25	0	5.68	0.5515	6	3	5	14
Norway	5	5	0	0.4	0.1848	0	0	0	0
Spain	9	4	5	1.11	0.2264	0	0	0	0
Sweden	40	38	2	1.08	0.2572	0	0	4	4
Switzerland	25	25	0	4.52	0.5188	4	6	1	11
Turkey	17	9	8	0	0.2059	0	0	0	0
United Kingdom	165	165	0	4.01	0.4172	25	15	21	61
All observations	528	488	40	3.36	0.3825	66	44	46	156

Panel B: Distributional statistics for the measurement and disclosure scores by year

		Measurement				Medals			
Year	Total observations	# Firm-years measuring IP at FV	# Firm-years measuring IP at AC	# Avg Number of EPRA Figures	Avg EPRA Overall Score	Gold	Silver	Bronze	Total
2009	97	90	7	1.29	0.2776	7	6	12	25
2010	103	96	7	2.63	0.3443	7	8	8	23
2011	108	100	8	3.46	0.3900	12	9	8	29
2012	110	101	9	4.22	0.4262	16	13	10	39
2013	110	101	9	4.92	0.4595	24	8	8	40
All observations	528	488	40	3.36	0.3825	66	44	46	156

The global sample comprises of 528 firm-year observations from 112 real estate firms in 16 countries between 2009 and 2013. Panel A shows distributional statistics for selected information by country. This includes (1) total observations; (2-3) the number of firm-years that recognize investment properties at fair value and historical cost, respectively; (4) the average number of EPRA figures disclosed; (5) the average EPRA overall score; and (6-9) and the number of medals that were awared by Deloitte in their EPRA annual report survey. Panel B shows the same distributional statistics by year.

Table 3.6: Value Relevance

Dependent variable		*PPS*							
		Relative Value Relevance						Incremental Value Relevance	
Variables	Predicted sign	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	?	0.829	6.705 *	4.059	-3.632	3.797	2.621	1.218	0.381
		(0.22)	(1.85)	(1.11)	(-0.75)	(0.47)	(0.32)	(0.31)	(0.10)
BVE_PS	+	0.791 ***			0.821 ***			0.646 ***	0.727 ***
		(12.15)			(6.29)			(9.24)	(8.67)
EPRA_NAV_PS	+		0.684 ***			0.732 ***			
			(18.02)			(9.54)			
EPRA_NNNAV_PS	+			0.757 ***			0.839 ***		
				(16.03)			(7.55)		
EPRA_NAV_PS - BVE_PS	+							0.502 ***	
								(3.62)	
EPRA_NNNAV_PS - BVE_PS	+								0.556 ***
									(4.69)
EPS	+	2.564 ***	3.622 ***	3.768 ***				5.278 ***	4.720 ***
		(4.40)	(7.81)	(8.82)				(3.62)	(3.02)
EPRA_EPS	+				3.501	4.114 **	3.540		
					(1.39)	(2.06)	(1.59)		
EPRA_EPS - EPS	+							2.134	1.456
								(1.61)	(1.01)
Year fixed effets		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2		0.9693	0.9829	0.9827	0.9615	0.9587	0.9532	0.9857	0.9846
Adj-R^2		0.9652	0.9806	0.9804	0.9563	0.9531	0.9469	0.9834	0.9822
N		120	120	120	120	120	120	120	120

This table reports OLS coefficient estimates and, in parentheses, t-statistics of Equation (1A) and (1B). We regress price per share (*PPS*) on different measures of equity value per share and periodical performance per share. *PPS* is the market capitalization four month after the fiscal year end divided by the number of common shares four months after the financial year end. NAV per share is measured using three different proxies: *BVE_PS* is book value of equity divided the number of common shares and *EPRA_[NN]NAV_PS* is the EPRA [triple] net asset value divided by the number of common shares as specified in EPRA (2010). Periodical performance per share is measured using *EPS*, defined as IFRS net income divided by the number of common shares, and *EPRA_EPS* as specified in EPRA (2010). We seek to investigate the relative and incremental value of EPRA_NAV_PS, EPRA_NNNAV_PS, and EPRA_EPS. T-statistics in parentheses are calculated using robust standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Table 3.7: Stock Liquidity and EPRA-BPR Compliance

Dependent variable		*Log(Spread)*					
		Medal		EPRA Overall Score		EPRA Performance Measures	
Variables	Predicted sign	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	?	-4.759 ***	-1.641 ***	-4.640 ***	-1.427 ***	-4.891 ***	-1.521 ***
		(-38.73)	(-3.43)	(-29.71)	(-3.07)	(-39.12)	(-3.10)
Medal	-	-1.076 ***	-0.427 ***				
		(-6.14)	(-3.25)				
EPRA Overall Score	-			-1.847 ***	-0.632 *		
				(-3.89)	(-2.09)		
EPRA Performance Measures	-					-0.115 ***	-0.039 *
						(-4.17)	(-2.14)
Vol	+		7.903 ***		7.419 ***		7.506 ***
			(2.85)		(2.63)		(2.64)
Turnover	-		-0.472 **		-0.482 *		-0.493 *
			(-2.09)		(-2.03)		(-2.07)
Size	-		-0.518 ***		-0.544 ***		-0.543 ***
			(-7.93)		(-8.34)		(-8.27)
Chs	-		-0.349 ***		-0.388 ***		-0.368 ***
			(-3.11)		(-3.27)		(-3.15)
LegalQuality	-		-0.079		-0.060		-0.064
			(-0.43)		(-0.32)		(-0.34)
Year fixed effets		Yes	Yes	Yes	Yes	Yes	Yes
R^2		0.2089	0.6474	0.1283	0.6335	0.1333	0.6338
Adj-R^2		0.2012	0.6404	0.1198	0.6262	0.1247	0.6265
F-statistic		21.96	48.75	17.06	34.2	16.98	35.51
N		515	515	515	515	515	515

This table reports OLS coefficient estimates and, in parentheses, t-statistics of Equation (3.2). We regress Log(*Spread*) on one of three proxies for EPRA BPR compliance (i.e., *Medal, EPRA Overall Score,* or *EPRA Performance Measures*) and control variables. *Log(Spread)* is the logarithmic transformation of the weekly median quoted bid-ask spread (i.e., the difference between the bid and ask price divided by the midpoint and measured at the end of each trading day) measured three month after the financial year end. We use three proxies for EPRA BPR compliance: In models 1-2, we use *Medal* , an indicator variable equal to one if firm's annual statement was awarded a medal in the EPRA Annual Report Survey and zero otherwise. In model 3-4, we use *EPRA Overall Score* , a self-constructed measure. In model 5-6, we use *EPRA Performance Measures* , the number of disclosed EPRA performance measures. Control variables include the following: *Vol* is the standard deviation of all weekly log returns during the financial year. *Turnover* is yearly turnover volume in a financial year divided by the average number of common shares outstanding. *Size* is the logarithmic transformation of market capitalization at the end of the financial year. *Chs* is an indicator variable equal to one if the number of closely held shares divided by the number of common shares outstanding at the financial year end is below the sample mean and zero otherwise. *LegalQuality* is the country-specific regulatory quality index by Kaufmann, Kraay, and Mastruzzi (2010) for each financial year. T-statistics in parentheses are calculated using robust standard errors clustered by firms. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Table 3.8: Refinancing Costs and EPRA-BPR Compliance

Dependent variable		*Log(COC)*					
		Medal		EPRA Overall Score		EPRA Performance Measures	
Variables	Predicted sign	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	?	-2.461 ***	-2.420 ***	-2.460 ***	-2.370 ***	-2.482 ***	-2.404 ***
		(-41.62)	(-7.29)	(-38.76)	(-7.20)	(-43.51)	(-7.28)
Medal	-	-0.185 ***	-0.107 *				
		(-2.78)	(-1.94)				
EPRA Overall Score	-			-0.261 *	-0.153		
				(-1.85)	(-1.21)		
EPRA Performance Measures	-					-0.025 ***	-0.013 *
						(-2.61)	(-1.75)
Vol	+		0.897		0.510		0.516
			(0.50)		(0.28)		(0.28)
Turnover	-		0.274 ***		0.273 **		0.270 **
			(2.62)		(2.55)		(2.56)
Size	-		-0.048		-0.054 *		-0.051 *
			(-1.59)		(-1.78)		(-1.71)
Chs	-		-0.112 **		-0.118 **		-0.113 **
			(-2.18)		(-2.24)		(-2.14)
LegalQuality	-		-0.195 *		-0.196 *		-0.191 *
			(-1.88)		(-1.87)		(-1.84)
FcBias	+		0.000		0.000		0.000
			(0.08)		(0.22)		(0.25)
Btm	?		0.196 ***		0.203 ***		0.203 ***
			(3.16)		(3.32)		(3.33)
Lev	+		0.201		0.212		0.203
			(0.98)		(1.00)		(0.97)
Roa	-		-0.010		-0.010		-0.011
			(-1.40)		(-1.41)		(-1.43)
Year fixed effets		Yes	Yes	Yes	Yes	Yes	Yes
R^2		0.0421	0.3622	0.0125	0.3558	0.0384	0.3596
Adj-R^2		0.0313	0.3416	0.0092	0.3350	0.0275	0.3389
F-statistic		3.71	5.01	2.81	4.88	3.91	5.27
N		449	449	449	449	449	449

This table reports OLS coefficient estimates and, in parentheses, t-statistics of Equation (3.3). We regress Log(*COC*) on one of three proxies for EPRA BPR compliance (i.e., *Medal*, *EPRA Overall Score,* or *EPRA Performance Measures*) and control variables. Following Hail and Leuz (2006), *Log(COC)* is the logarithmic transformation of the mean cost of capital calculated in accordance with four different model specifications suggested in (1) Claus and Thomas (2001), (2) Gebhardt, Lee and Swaminathan (2001), (3) Ohlson and Juettner-Nauroth (2005), and (4) Easton (2004). We use three proxies for EPRA BPR compliance: In models 1-2, we use *Medal*, an indicator variable equal to one if firm's annual statement was awarded a medal in the EPRA Annual Report Survey and zero otherwise. In model 3-4, we use *EPRA Overall Score*, a self-constructed measure. In model 5-6, we use *EPRA Performance Measures*, the number of disclosed EPRA performance measures. Control variables include the following: *Vol* is the standard deviation of all weekly log returns during the financial year. *Turnover* is the yearly turnover volume in a financial year divided by the average number of common shares outstanding. *Size* is the logarithmic transformation of the market capitalization at the financial year end. *Chs* is an indicator variable equal to one if the number of closely held shares divided by the number of common shares outstanding at the financial year end is below the sample mean and zero otherwise. *LegalQuality* is the country-specific regulatory quality index by Kaufmann, Kraay, and Mastruzzi (2010) for each financial year. *FcBias* is the difference between the mean financial year end earnings forecast eleven months before the financial year end and the actual earnings as stated in the financial statements. *Btm* is the book value of equity divided by the market value of equity at the financial year end. *Lev* is total liabilities divided by total assets at the financial year end. *Roa* is the net income divided by the average total assets in a financial year. T-statistics in parentheses are calculated using robust standard errors clustered by firms. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Table 3.9: Analysts Coverage and EPRA-BPR Compliance

Dependent variable		*AnaCov*					
		Medal		EPRA Overall Score		EPRA Performance Measures	
Variables	Predicted sign	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	?	4.360 ***	-15.467 ***	4.076 ***	-17.063 ***	5.230 ***	-16.123 ***
		(8.49)	(-6.27)	(6.50)	(-6.37)	(9.95)	(-6.01)
Medal	+	6.170 ***	3.580 ***				
		(6.88)	(4.92)				
EPRA Overall Score	+			9.196 ***	4.494 **		
				(3.89)	(2.54)		
EPRA Performance Measures	+					0.641 ***	0.343 **
						(4.69)	(3.24)
Vol	+		34.990 **		46.077 ***		45.340 ***
			(2.41)		(2.63)		(2.69)
Turnover	+		1.007 **		1.044 **		1.121 **
			(2.39)		(2.09)		(2.24)
Size	+		2.305 ***		2.525 ***		2.478 ***
			(6.47)		(6.50)		(6.60)
Chs	+		1.213 **		1.458 **		1.298 *
			(1.97)		(2.17)		(1.94)
LegalQuality	+		0.194		1.128		1.080
			(1.20)		(1.07)		(1.03)
FcBias	-		-0.051 ***		-0.058 ***		-0.058 ***
			(-3.08)		(-3.65)		(-3.65)
Btm	+		1.894		-0.031		-0.005
			(0.38)		(-0.05)		(-0.01)
Lev	+		0.042		1.382		1.365
			(0.97)		(0.62)		(0.62)
Roa	+		1.121		0.040		0.041
			(0.90)		(0.74)		(0.76)
Year fixed effets		Yes	Yes	Yes	Yes	Yes	Yes
R^2		0.2699	0.5812	0.117	0.5289	0.153	0.5423
Adj-R^2		0.2625	0.5690	0.1080	0.5152	0.1444	0.5291
F-statistic		15.38	24.63	11.44	13.77	16.65	15.99
N		497	497	497	497	497	497

This table reports OLS coefficient estimates and, in parentheses, t-statistics of Equation (3.4). We regress *AnaCov* on one of three proxies for EPRA BPR compliance (i.e., *Medal, EPRA Overall Score,* or *EPRA Performance Measures*) and control variables. *AnaCov* is the number of analysts following a firm three months after the financial year end. We use three proxies for EPRA BPR compliance: In models 1-2, we use *Medal*, an indicator variable equal to one if firm's annual statement was awarded a medal in the EPRA Annual Report Survey and zero otherwise. In model 3-4, we use *EPRA Overall Score,* a self-constructed measure. In model 5-6, we use *EPRA Performance Measures,* the number of disclosed EPRA performance measures. Control variables include the following: *Vol* is the standard deviation of all weekly log returns during the financial year. *Turnover* is the yearly turnover volume in a financial year divided by the average number of common shares outstanding. *Size* is the logarithmic transformation of the market capitalization at the financial year end. *Chs* is an indicator variable equal to one if the number of closely held shares divided by the number of common shares outstanding at the financial year end is below the sample mean and zero otherwise. *LegalQuality* is the country-specific regulatory quality index by Kaufmann, Kraay, and Mastruzzi (2010) for each financial year. *FcBias* is the difference between the mean financial year end earnings forecast eleven months before the financial year end and the actual earnings as stated in the financial statements. *Btm* is the book value of equity divided by the market value of equity at the financial year end. *Lev* is total liabilities divided by total assets at the financial year end. *Roa* is the net income divided by the average total assets in a financial year. T-statistics in parentheses are calculated using robust standard errors clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Table 3.10: Within-Firm Analysis

		Log(Spread)	Log(COC)	AnaCov
Variables	Predicted sign	(1)	(2)	(3)
Intercept	?	-2.779 **	-1.721 ***	-2.521
		(-2.05)	(-3.75)	(-0.40)
EPRA Application	-,-,+	-0.402 **	0.040	3.831 ***
		(-2.08)	(0.50)	(2.78)
Notes_Pages	-,-,+	-0.024 **	-0.002	0.041
		(-2.06)	(-0.61)	(0.68)
Vol	+,+,?	-3.601	3.141	97.058 **
		(-0.34)	(1.05)	(2.20)
LegalQuality	-,-,+	-0.838	-0.585 **	0.045
		(-1.42)	(-2.45)	(0.01)
Log(Returns)	-,-,+	-1.596 **	-0.520	10.409 **
		(-2.11)	(-1.64)	(2.56)
Year fixed effets		Yes	Yes	Yes
R^2		0.2216	0.2667	0.2668
Adj-R^2		0.1632	0.2072	0.2118
F-statistic		6.58	3.31	4.71
N		130	121	130

This table reports OLS coefficient estimates and, in parentheses, t-statistics. The regressions only include firms that became compliant to EPRA BPR during the sample period, i.e., firms for which we have observation before and after EPRA BPR adoption. We regress Log(*Spread*), Log(*COC*), and *AnaCov* on *EPRA Application* and control variables. *EPRA Application* is an indicator variable equal to one if firms received either a gold or silver medal in Deloitte's EPRA Annual Report Survey in the time period between 2009 and 2013 and zero otherwise. For the definitions of the dependent variables and control variables refer to Appendix 3.A. T-statistics in parentheses are calculated using robust standard errors clustered by firms.***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Table 3.11: Switch-back Analysis

		Log(Spread)	Log(COC)	AnaCov
Variables	Predicted sign	(1)	(2)	(3)
Intercept	?	-5.948 **	-1.843 ***	19.529
		(-2.15)	(-3.23)	(1.03)
SwitchBack	+,+,-	0.816 ***	-0.011	-4.195 **
		(3.02)	(-0.10)	(-2.39)
Non_adoption	+,+,-	0.782	0.286	-6.734 *
		(1.37)	(1.35)	(-1.86)
Notes_Pages	-,-,+	-0.001	-0.003	-0.026
		(-0.10)	(-0.70)	(-0.42)
Vol	+,+,?	18.095	3.580	-146.884 *
		(1.52)	(0.61)	(-1.89)
LegalQuality	-,-,+	-0.051	-0.438	-2.538
		(-0.04)	(-1.49)	(-0.29)
Log(Returns)	-,-,+	-2.024 ***	-0.503	11.555 **
		(-2.60)	(-1.01)	(2.50)
Year fixed effets		Yes	Yes	Yes
R^2		0.3605	0.3009	0.3344
Adj-R^2		0.2046	0.1304	0.1720
F-statistic		16.27	8.31	684.68
N		52	52	52

This table reports OLS coefficient estimates and, in parentheses, t-statistics. The regressions only include firms that received a silver or gold accreditation during at least one year in our sample period and lost the silver or gold accreditation subsequently. We regress Log(*Spread*), Log(*COC*), and *AnaCov* on *SwitchBack*, *Non_adoption* and control variables. *SwitchBack* is an indicator variable equal to one for the time period when firms lose their gold or silver accreditation until they again receive silver or gold accreditation according to Deloitte's EPRA Annual Report Survey and zero otherwise. *Non_adoption* is an indicator variable equal to one from the start of the sample period (2009) until they first receive gold or silver accreditation according to Deloitte's EPRA Annual Report Survey and zero otherwise. For the definitions of the dependent variables and control variables refer to Appendix 3.A. T-statistics in parentheses are calculated using robust standard errors clustered by firms. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Table 3.12: Determinants of EPRA Adoption, Application, and Compliance

		Probit		OLS	
Dependent variable		EPRA Adoption	EPRA Application	EPRA Overall Score	EPRA Performance Measures
Variables	Predicted sign	(1)	(2)	(3)	(4)
Intercept	?	0.788	-2.277	-0.275 **	-3.704 **
		(0.34)	(-0.20)	(-2.48)	(-2.30)
Size	+	0.129	0.460 ***	0.036 ***	0.645 ***
		(1.46)	(6.49)	(5.10)	(5.23)
Btm	?	-0.210	0.035	0.017	0.208
		(-0.77)	(0.25)	(0.98)	(0.92)
Vol	?	-0.210 ***	-4.937	-0.651 *	-8.638 *
		(-3.00)	(-1.27)	(-1.89)	(-1.70)
Log(Returns)	?	-0.951	-0.495	-0.121 ***	-1.611 ***
		(-1.63)	(-1.59)	(-3.56)	(-3.08)
DebtOffering	+	0.554 **	0.566 ***	0.065 **	0.759 *
		(2.05)	(3.45)	(2.38)	(1.71)
SeasonedEquityOffering	+	-0.030	0.144	0.015	0.276
		(-0.12)	(0.96)	(0.80)	(0.94)
LegalQuality	+	-0.545 **	0.252	0.081 ***	1.429 ***
		(-1.99)	(1.16)	(3.44)	(3.78)
Number_of_EPRA_adopters	+	-0.019	-0.049 *	0.005 **	-0.013
		(-0.76)	(-1.83)	(2.11)	(-0.52)
Year fixed effets		Yes	Yes	Yes	Yes
Pseudo-R^2 / R^2		0.1292	0.2116	0.1871	0.2360
Wald-Chi² / F-statistic		25.19	92.72	14.99	15.34
N		322	512	512	512

This table reports Probit (1-2) and OLS (3-4) coefficient estimates and, in parentheses, t-statistics of Equation (3.5) and (3.6). We regress *EPRA Adoption* , *EPRA Application* , *EPRA Overall Score* , and *EPRA Performance Measures* on potential determinants. *EPRA Adoption* is an indicator variable equal to one when firms received their first silver or gold medal in Deloitte's EPRA Annual Report Survey for the time period between 2010 and 2013 and zero otherwise. *EPRA Application* is an indicator variable equal to one if firms received either a gold or silver medal in Deloitte's EPRA Annual Report Survey in the time period between 2009 and 2013 and zero otherwise. *EPRA Overall Score* is a self-constructed measure to proxy for the extent to which firms comply with EPRA BPR. *EPRA Performance Measures* is the number of disclosed EPRA performance measures in their annual report. Potential determinants include the following: *Size* is the logarithmic transformation of the market capitalization at the financial year end. *Btm* is the book value of equity divided by the market value of equity at the financial year end. *Vol* is the standard deviation of all weekly log returns during the financial year. *Log(Returns)* is the logarithmic transformation of the relative share price performance in the financial year. *DebtOffering* is an indicator variable equal to one if a firm experienced a debt issuance in the following financial year and zero otherwise. *SeasonedEquityOfferings* is an indicator variable equal to one if a firm experienced an SEO in the following year or zero otherwise. *LegalQuality* is the country-specific regulatory quality index by Kaufmann, Kraay, and Mastruzzi (2010) for each financial year. *Number_of_EPRA_adopters* is the numbers of firms in our sample that disclosed at least one EPRA performance measure in that financial year. T-statistics in parentheses are calculated using robust standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Appendix 3

Appendix 3.A: Variable Definition

Variables	Indicator/ Continous	Definition
Disclosure measurement		
Medal	Ind.	An indicator variable equal to one if firm's annual statement was awarded any medal in the Annual Report Survey conducted by Deloitte and zero otherwise.
Gold	Ind.	An indicator variable equal to one if firm's annual statement was awarded a gold medal in the Annual Report Survey conducted by Deloitte and zero otherwise.
Silver	Ind.	An indicator variable equal to one if firm's annual statement was awarded a silver medal in the Annual Report Survey conducted by Deloitte and zero otherwise.
Bronze	Ind.	An indicator variable equal to one if firm's annual statement was awarded a bronze medal in the Annual Report Survey conducted by Deloitte and zero otherwise.
EPRA Overall Score	Cont.	A self-constructed measure to proxy for the extent to which firms comply with EPRA BPR.
EPRA Performance Measures	Cont.	The number of disclosed EPRA performance measures in an annual report.
EPRA Adoption	Ind.	An indicator variable equal to one when firms received their first silver or gold medal in Deloitte's EPRA Annual Report Survey for the time period between 2010 and 2013 and zero otherwise.
EPRA Application	Ind.	An indicator variable equal to one in each year firms received either a silver or gold medal in Deloitte's EPRA Annual Report Survey and zero otherwise.
SwitchBack	Ind.	An indicator variable equal to one for the time period when firms lose their gold or silver accreditation until they again receive silver or gold accreditation according to Deloitte's EPRA Annual Report Survey and zero otherwise.
Non_Adoption	Ind.	An indicator variable equal to from the start of the sample period (2009) until they first receive gold or silver accreditation according to Deloitte's EPRA Annual Report Survey and zero otherwise.
Mechanisms		
Log(*Spread*)	Cont.	The logarithmic transformation of the weekly median quoted bid-ask spread (i.e., difference between the bid and ask price divided by the midpoint and measured at the end of each trading day) measured three month after the financial year end.
Log(*COC*)	Cont.	Following Hail and Leuz (2006), log(COC) is the logarithmic transformation of the mean costs of capital calculated in accordance with four different model specifications suggested in (1) Claus and Thomas (2001), (2) Gebhardt, Lee and Swaminathan (2001), (3) Ohlson and Juettner-Nauroth (2005), and (4) Easton (2004).
AnaCov	Cont.	The number of analysts that follow a firm three months after the financial year end.
Value Relevance		
PPS	Cont.	The market capitalization four months after the financial year end divided by the number of common shares at that time.
BVE_PS	Cont.	The book value of equity divided by the number of common shares four months after the financial year end.
EPRA_NAV_PS	Cont.	The EPRA net asset value divided by the number of common shares four months after the financial year end.
EPRA_NNNAV_PS	Cont.	The EPRA triple net asset value divided by the number of common shares four months after the financial year end.
EPS	Cont.	The net income divided by the number of common shares four months after the financial year end.
EPRA_EPS	Cont.	The EPRA earnings divided by the number of common shares four months after the financial year end.
Liquidity controls		
Vol	Cont.	The standard deviation of the weekly log returns during the financial year.
Turnover	Cont.	The yearly turnover volume in the financial year divided by the average number of common shares outstanding.
Size	Cont.	The logarithmic transformation of the market capitalization at the financial year end.
Chs	Cont.	An indicator variable equal to one if the number of closely held shares divided by the number of common shares outstanding at the financial year end is below the sample mean and zero otherwise.
LegalQuality	Cont.	The country-specific regulatory quality index by Kaufmann, Kraay, and Mastruzzi (2010) for each financial year.
Additional controls		
FcBias	Cont.	The difference between the mean financial year end earnings forecast eleven month before the financial year end and the actual earnings as stated in the financial statements.
Btm	Cont.	The book value of equity divided by the market value of equity at the the financial year end.
Lev	Cont.	The total liabilities divided by the total assets at the financial year end.
Roa	Cont.	The net income divided by the average total assets in a financial year.
Others		
Log(Returns)	Cont.	The logarithmic transformation of the relative share price performance plus one in the financial year.
Notes_Pages	Cont.	The number of pages of the financial statement notes in an annual report.
SeasonedEquityOffering	Ind.	An indicator variable equal to one if a firm experienced an SEO in the following year and zero otherwise.
DebtOffering	Ind.	An indicator variable equal to one if a firm experienced a debt issuance in the following financial year and zero otherwise.