Are International Accounting Standards more Credit Relevant than Domestic Standards?

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ABSTRACT

We examine whether the credit relevance of financial statements, defined as the ability of accounting numbers to explain credit ratings, is higher after firms are required to report under International Financial Reporting Standards (IFRS). We find an improvement in credit relevance for firms in seventeen countries after mandatory IFRS reporting is introduced in 2005; this increase is higher than that reported for a matched sample of US firms. The increase in credit relevance is particularly pronounced for higher risk speculative-grade issuers, where accounting information is predicted to be more important; and for IFRS adopters with large first-time reconciliations, where the impact of IFRS is expected to be greater. These tests provide reassurance that the overall enhancement in estimated credit relevance is driven by accounting changes related to IFRS adoption. Our results suggest that credit rating analysts' views of economic fundamentals are more closely aligned with IFRS numbers, and that analysts anticipate at least some of the effects of the IFRS transition.

Keywords: *IFRS; debt markets; credit ratings; credit relevance.*

JEL Classifications: *G15, G33, K20, M41, M48.*

1. Introduction

Debt markets are a more important source of new capital for companies than equity markets (Henderson et al. 2006); and accounting standard setters recognize that creditors are an important financial statement user group (e.g. International Accounting Standards Board 2015).[1] Yet comparatively little is known about how well financial statements address creditors' needs, especially in the international context. Research confirms that US GAAP information is important in the credit rating process (Blume et al. 1998, Hann et al. 2007) and in bond pricing (Easton et al. 2009). But recent requirements for firms in many countries to report under IFRS have not been evaluated from a credit market perspective, with most studies on the relevance of IFRS accounting numbers focusing on the equity market perspective (e.g. Barth et al. 2008, Barth et al. 2012). Since creditors' decisions and information needs differ from those of equity investors (Holthausen and Watts 2001, Hann et al. 2007), evidence that IFRS is relevant to equity markets does not imply relevance for creditors.

In this paper we compare the credit relevance of financial statement numbers prepared under IFRS and under domestic accounting standards for a sample of firms that are required to switch to IFRS reporting in 2005. We follow Hann et al. (2007) in defining credit relevance as the ability of accounting numbers to explain credit analysts' ratings. We show that IFRS financial statements capture information used by rating analysts better than financial statements prepared under domestic standards. Our results also suggest that credit rating analysts understand

[1] For example, during the 2000-2011 period, the average European country's corporate debt market was three times the size of its equity market; the balance between private sector debt and equity in other non-EU countries over the same period was comparable. In particular, over 2000-2011 the total amount of debt in the EU was 193 percent (as a percentage of GDP), whereas the total value of all shares listed on European stock markets was 59 percent. Similarly, the total amount of US corporate debt over the same period was 323 percent as opposed to the total market capitalization of stocks which was 126 percent (for further details see World Bank, Global Financial Development Database).

the limitations of domestic accounting standards and anticipate some of the changes resulting from IFRS adoption.

Because general purpose financial reporting standards can require standard setters to trade-off the interests of different user groups, there is a degree of ambiguity concerning the relevance of IFRS to creditors. On the one hand, some IFRS requirements are expected to enhance the information available to creditors, e.g. the recognition of previously unrecognized pension deficits under IAS 19 provides more information on effective debt obligations; and impairment accounting under IAS 36 leads to more timely loss recognition (Ball et al. 2008). On the other hand, IFRS requires or permits fair valuation of many assets and liabilities and this might be inconsistent with creditors' needs if it results in the recognition of economic gains before realization occurs or to the understatement of the carrying value of debt relative to contractual obligations. While such accounting treatments are argued by some to be consistent with equity investors' needs, they undermine the usefulness of financial statements to creditors (Schipper 2005, Ball et al. 2008). Additionally, IFRS often requires preparers to exercise a high degree of judgment and estimation, producing less verifiable and less reliable accounting numbers and creating opportunities for opportunistic manipulation of financial statements (Ball et al. 2015); for example, firms that choose the fair value measurement basis for their non-financial assets under IAS 16 provide potentially less reliable asset values and therefore less credit relevant information. In light of such doubts about whether IFRS enhances the usefulness of financial statements for creditors, the question of how the credit relevance of financial statements changes in the switch from domestic accounting standards to IFRS is essentially an empirical issue.

Our analysis is based on an international sample of firms from seventeen countries which mandated IFRS for the first time in 2005 and for which long-term issuer credit ratings are available from Standard & Poor's (S&P). In line with prior studies we use credit ratings as a surrogate for estimated default risk and employ a model that includes only accounting variables, because our interest is in assessing the ability of accounting fundamentals to capture attributes considered relevant by rating analysts (Blume et al. 1998, Hann et al. 2007, Jorion et al. 2009). As in Hann et al. (2007) we estimate credit relevance using the explanatory power (the pseudo-R^2) of an accounting-based credit rating model estimated by ordered probit.

In baseline tests we find that the explanatory power of the credit rating model increases by a modest 2.5 percentage points in the post-IFRS adoption period. We also document that the accuracy of probabilistic forecasts of credit ratings for mandatory IFRS adopters improves after the adoption. Next, in line with Barth et al. (2012), we perform comparative analysis using a sample of a contemporaneously matched US firms reporting under US GAAP and show that the increase in credit relevance for IFRS adopting firms is higher than the improvement in credit relevance for their US peers. Inferences remain qualitatively unchanged when we compare IFRS adopters to the full population of US firms with S&P credit ratings. Results remain robust to further analysis, including alternative samples, rating model specifications and credit relevance metrics. We interpret our findings as showing that relative to domestic standards, IFRS financial statement numbers map more closely onto latent attributes assessed by credit analysts.

To improve confidence that our baseline results are capturing effects related to the accounting standards regime change, we conduct two further sets of analysis. First, based on prior research findings that accounting numbers are more relevant to creditors when the likelihood of borrower default is higher (e.g. De Franco et al. 2009), we predict that IFRS-related changes in credit relevance will be higher when firms have higher default risk. Results support this prediction – the increase in credit relevance associated with IFRS adoption is twice as high for speculative-grade firms compared to investment-grade firms.

Second, we predict that IFRS-related changes in credit relevance should be greatest when the switch from domestic standards to IFRS results in relatively large changes to the credit ratings model inputs. Similar to Horton et al. (2013) we exploit the requirement under IFRS 1 for first-time IFRS adopters to restate and reconcile to IFRS the financial statements prepared under domestic accounting standards in the previous year. Based on line item reconciliations between domestic standards and IFRS we develop firm-level measures of the distance between local GAAP and IFRS. Results show that when first-time IFRS reconciliations are small (i.e. when domestic GAAP accounting numbers are relatively close to IFRS numbers) credit relevance in the pre-IFRS period is considerably higher than when reconciliations are large; this finding suggests that financial statements prepared under domestic standards can be relatively successful in capturing the fundamentals of concern to credit rating analysts when firm-level accounting numbers are close to IFRS. We also find that credit relevance increases between the pre-IFRS and the post-IFRS periods only for firms with large first-time IFRS reconciliation differences, i.e. where the expected impact of IFRS adoption is greatest. Finally, when we focus on the IFRS transition year alone, credit ratings are better explained by IFRS-restated accounting numbers than by domestic standard accounting numbers only for issuers where the differences between domestic standards and IFRS are large; this result suggests that credit analysts are able to estimate at least some of the accounting differences associated with IFRS transition and that these differences are considered relevant in credit rating decisions. The analysis based on first-time reconciliations of firms is informative because it demonstrates that changes in credit relevance are associated with de facto accounting changes, assessed from the perspective of the credit analyst.

Broadly, our study contributes to the growing literature on the consequences of IFRS financial reporting for debt markets by considering changes in the credit relevance of accounting information linked to mandatory IFRS adoption.[2] Our paper is most closely related to the study of Wu and Zhang (2014) who examine changes in the sensitivity of credit ratings to accounting numbers for IFRS adopters; they find that credit ratings are more sensitive to an accounting default factor after mandatory IFRS adoption, but only in countries with strong rule of law. Bhat et al. (2014) conduct a similar analysis relating the sensitivity of credit default swap rates to earnings, book value and leverage; contrary to Wu and Zhang (2014) they find no evidence that mandatory IFRS adoption affects the sensitivity of credit default swaps to accounting earnings. Our research focus differs because credit relevance captures the extent to which financial statement numbers *explain* credit ratings. In contrast, changes in the estimated sensitivity (slope coefficients) in a credit rating (or credit default swap rate) model do not necessarily imply changes in credit relevance.[3] For this reason, we are agnostic about the magnitude and changes of values of slope coefficients and focus on the ability of accounting numbers to explain variation in credit ratings.[4]

Overall, our analysis points to credit rating analysts displaying a degree of accounting sophistication in their decision making (Standard & Poor's 2008, Moody's 2010, Kraft 2015).

[2] For studies of the implications of IFRS adoption for financing decisions and debt security valuation, see e.g. Florou and Kosi (2015) and Naranjo et al. (2015); for studies of the consequences of IFRS adoption for debt contracting see Chen et al. (2013), Ball et al. (2015) and Brown (2016).

[3] Slope coefficients are a function of the underlying measurement scales of variables as well as the degree to which economic attributes are captured by accounting numbers. For example, if IFRS numbers are a constant multiple of domestic standards numbers, slope coefficients will change by a factor proportional to that multiple. But this does not imply that explanatory power (credit relevance) changes.

[4] Similar to Bhat et al. (2014), in a recent working paper Kraft and Landsman (2014) examine the effects of mandatory IFRS adoption on accounting-based prediction models for CDS spreads.

Our paper suggests that credit rating analysts understand how accounting measurement rules differ across accounting standards regimes and that they do not mechanistically use accounting numbers in determining credit ratings. Based on the assumption that ratings depend on assessment of the economic fundamentals of firms, the evidence we report is consistent with financial statement numbers prepared under IFRS better capturing the economic fundamentals that matter for credit ratings. In view of the importance of credit ratings in the market pricing of debt, our results complement prior results on the decision relevance of IFRS accounting numbers for equity markets obtained by Barth et al. (2008, 2012).

The remainder of the paper is organized as follows. In the next section we provide a brief overview of related literature. Section 3 elaborates on our research design. Section 4 outlines the sample construction and describes the data. In Section 5 we present our empirical findings. Section 6 concludes.

2. Theoretical background and motivation

2.1. *IFRS and credit relevance*

Several prior studies document differences between IFRS and domestic accounting standards in respect of both measurement and recognition rules, and in disclosure requirements (e.g. Ding et al. 2007, Bae et al. 2008). IFRS are predicted to improve financial reporting because of more extensive and informative disclosures, better measurement and recognition rules and enhanced comparability (Hail et al. 2010). The potential benefits from IFRS due to enhanced disclosures may be less important to solicited rating analysts because they can mitigate weak public disclosure through access to private information provided directly by issuers (Jorion et al. 2005, Frost 2007, De Franco et al. 2009). Because rating analysts have private access to issuers, we expect that credit relevance effects of IFRS will derive primarily from improved recognition and measurement and improved accounting comparability.

Credit ratings are designed to inform debt market participants interested in assessing the ability of borrowers to service future debt obligations. Hence the economic fundamentals of importance to creditors include the future cash flow prospects of a borrower relative to its debt obligations, the risk of a borrower defaulting on its debt obligations and the values of a borrower's assets that could be liquidated to meet debt obligations if future cash flows are insufficient to meet debt obligations. Asset values are also important when debt contracts include collateral provisions (Armstrong et al. 2010). Therefore, financial statements will be useful to creditors and credit rating analysts if they contain information that is useful in the prediction of future cash flows or if they provide reliable estimates of asset and liability values (Watts 2003).

Financial statements prepared under IFRS seek to achieve two important qualitative characteristics affecting the usefulness of accounting numbers to creditors: decision relevance (in forecasting future cash flows and net asset values) and representational faithfulness (International Accounting Standards Board 2015). Fair value accounting methods are an important feature of IFRS that is often motivated by reference to these two characteristics. Fair value accounting is required in accounting for many categories of financial instruments under IFRS 9, and available as an option for other categories of assets and liabilities, including property plant and equipment under IAS 16 and investment property under IAS 39. On the one hand, fair value accounting results in more timely recognition of economic gains and losses in financial statements, resulting in more relevant balance sheet values; on the other hand, it can lead to less informative net income measurement because fair value gains and losses are transitory in nature, reducing the usefulness of net income in forecasting future cash flows and future debt servicing capacity (Ball et al. 2015). Fair value accounting under IFRS 9 can also result in the understatement of the book value of debt relative to its redemption value if a borrower's issued debt is measured at fair value (Schipper 2005, Ball et al. 2008). Fair value accounting is also a potential source of concern for creditors because some fair valued balance sheet items can be less useful when based on difficult-to-verify inputs requiring management judgement and estimates as inputs to valuation models used if liquid market prices are not observable (Ball et al. 2015).

Accounting rules governing assets carried at amortized historical cost are less likely to be relevant because carrying values are generally different from economic values. But impairment tests applied under IAS 36 should ensure relatively timely recognition of economic losses and ensure alignment of carrying value with economic value when economic values fall below historical cost carrying amounts. Such asymmetric re-measurement of asset values is relevant to creditors because the values of debt claims are more sensitive to economic losses than to economic gains (Ball et al. 2008). But again, relevance may be compromised because management judgments and estimates are required in the calculation of recoverable amounts.

Harmonised financial reporting under IFRS also aims to produce more comparable financial statements. Potential comparability effects can influence estimated credit relevance in an international setting via two main channels. First, when reporting is under domestic accounting standards, differences in recognition and measurement rules across countries represent a source of country-level idiosyncratic measurement error in accounting numbers relative to the fundamental economic attributes assessed by rating analysts. This measurement error has a negative effect on estimated credit relevance. When all issuers report under IFRS, financial statements should be more comparable across countries, even if they do not capture economic fundamentals perfectly due to measurement and recognition properties of IFRS or cross-country differences in reporting incentives and enforcement. Subject to these qualifications, country-level recognition and measurement effects attributable to local GAAP are eliminated, leading us to expect higher credit relevance under IFRS since accounting numbers should map more closely on to the economic fundamentals on average. The second channel through which comparability effects might influence credit relevance is linked to the importance of peer comparisons in the credit rating process (Standard & Poor's 2008). Country or industry peer comparisons are informative because they contribute to identification of common trends in economic fundamentals, and any expansion in the set of comparable issuers potentially generates richer information on which to make credit rating assessments. This channel for comparability effects suggests that credit ratings could change as a result of enhanced information.

Our empirical tests establish whether financial statement numbers produced under IFRS explain credit ratings better than accounting numbers produced under domestic standards. Credit relevance tests assume that credit ratings reflect analysts' assessments of the likelihood that issuers will default, and if default occurs the expected recovery rate of amounts in arrears. Expectations are conditional on analysts' understanding of the economic position and performance of issuers informed by the public disclosures of issuers, including financial statements, and private communications between credit rating analysts and issuers. IFRS will be more credit relevant than domestic accounting standards if IFRS financial statement numbers capture the economic fundamentals determining credit ratings more reliably than numbers prepared under domestic standards.

Observing increased credit relevance after the adoption of IFRS does not necessarily imply that IFRS adoption causes analysts to revise their assessments of economic fundamentals –

hence it does not imply that credit ratings change. The reason for this is that IFRS reporting could effectively bring into the public domain information that was previously obtained by rating analysts through private communications with the borrower (Jorion et al. 2005, Frost 2007, De Franco et al. 2009). For example, IFRS reporting enhances transparency relating to pension assets, liabilities and deficits in many countries; it is quite likely that prior to IFRS adoption rating analysts obtained pensions-related information through communications with the borrower when domestic accounting standards did not require such disclosures. However, if IFRS adoption does provide new information to rating analysts beyond domestic accounting standards and private communications with borrowers, then this would be a further channel positively affecting credit relevance as well as, potentially, credit ratings.[5]

2.2. *Proximity to default and credit relevance*

Holders of debt securities receive payoffs that are non-linear in the value of firms' assets. When the value of assets is higher than the value of debt obligations, the holders of debt securities receive only the cash flows specified in debt contracts. However, when borrowers default, cash flows to debt holders are less than specified contractually. Consequently the value of debt is less sensitive to positive news than to negative news, leading to debt market demand for accounting information being asymmetric (Ball et al. 2008). Consistent with these arguments, prior research has found that bond price sensitivity to news about firm fundamentals is greatest when default risk is relatively high. For example, Easton et al. (2009) document a larger reaction of bond prices to earnings announcements for speculative-grade bonds; De Franco et al. (2009) provide evidence of greater reaction of bond market trading volume and returns to bond analysts' reports

[5] In a 2004 report anticipating the transition to IFRS reporting in Europe Standard & Poor's stated that they were not expecting any widespread or significant rating actions due to IFRS adoption (Standard & Poor's 2004).

for low-rated bonds; and Givoly et al. (2013) find higher explanatory power of an accounting-based bond returns model for higher yield bonds.

In our empirical tests we build on these insights by examining whether changes in the ability of accounting numbers to explain credit ratings across the pre- and post-IFRS periods differs between investment- and speculative-grade firms. If IFRS are more informative and if fundamental accounting factors are more important when the proximity to default is higher, changes in credit relevance associated with IFRS should be higher for speculative-grade firms.

2.3. *Materiality of accounting differences*

IFRS 1 *First-Time Adoption of IFRS* requires firms to reconcile prior year accounting numbers prepared under domestic accounting standards to IFRS when they switch from domestic accounting standards to IFRS. We exploit the first-time reconciliations as firm-level measures of de facto divergence between domestic accounting standards and IFRS assuming that higher divergence will lead to larger firm-specific reconciliations. We make three main predictions relating estimated credit relevance and changes in credit relevance to the magnitude of reconciliations. First, if IFRS financial statements better capture the economic fundamentals underlying credit ratings than domestic accounting standards then estimated credit relevance in the pre-IFRS period should be higher for borrowers with relatively small first-time reconciliations; second, when first-time reconciliations are relatively large, IFRS-restated accounting amounts for the year prior to IFRS adoption should better explain credit ratings in that year than accounting amounts prepared under domestic standards; and third, the increase in the informativeness of financial statements following the switch to IFRS should be higher for firms with larger first-time reconciliations (Brochet et al. 2013, Horton et al. 2013).

3. Research design

3.1. *Estimating credit relevance*

We follow Hann et al. (2007) and define credit relevance as the ability of financial statement numbers to explain default probabilities, using S&P long-term issuer credit rating as a proxy for default risk. Issuer credit ratings are an adequate proxy for default risk for at least three reasons: (a) they have been shown to be associated with *ex post* payment defaults and bond yields (Liu et al. 1999, Standard & Poor's 2008, Jorion et al. 2009); (b) they are determined by rating agencies' professional assessments of the probability distribution of future cash flows to debt holders (Ashbaugh-Skaife et al. 2006); and (c) in contrast to issue-level credit ratings, they indicate the probability of default for the entire firm regardless of the degree of protection afforded to holders of specific debt instruments (Cheng and Subramanyam 2008).

We employ the following empirical model predicting credit ratings as a function of contemporaneous financial statement numbers (Blume et al. 1998, Ashbaugh-Skaife et al. 2006, Hann et al. 2007, Jorion et al. 2009):[6]

$$Rating = f\,(IntCov1, IntCov2, IntCov3, IntCov4, ROA, LTD\ Leverage, TD\ Leverage, Size, CI, Loss) \quad (1)$$

In line with most prior studies, which collapse multiple ratings into fewer categories (e.g. Ashbaugh-Skaife et al. 2006, Jorion et al. 2009), the dependent variable, *Rating*, is Standard & Poor's long-term issuer credit rating at the end of fiscal year *t*, coded as ordered numerical values from 1 (CC) to 8 (AAA) so that credit ratings assigned higher numerical scores are assessed as

[6] Consistent with prior studies (Hann et al. 2007; Jorion et al. 2009) we exclude non-accounting variables (e.g. equity beta and equity volatility). This choice is justified by our research objective of comparing the credit relevance of financial statements prepared under different accounting regimes. However, we assess the robustness of our results to the inclusion of market-based factors in Section 5.2. For earlier research on the determinants of credit ratings see Horrigan (1966), West (1970) and Kaplan and Urwitz (1979).

having higher credit quality. The explanatory variables are based on published financial statement numbers and have been found to be important in prior research: interest coverage is coded to allow for non-linear effects as proposed by Blume et al. (1998) and Jorion et al. (2009) (*IntCov*1, *IntCov*2, *IntCov*3, *IntCov*4);[7] profitability, measured by return on assets (*ROA*); long-term debt leverage (*LTD Leverage*) and total debt leverage (*TD Leverage*); total assets, a proxy for firm size (*Size*); capital intensity (*CI*); and a loss indicator equal to one if the firm has negative earnings in the current and prior fiscal years, and zero otherwise (*Loss*). Prior research finds that credit ratings are positively related to interest coverage, profitability, firm size and capital intensity; and negatively related to both measures of leverage and to the loss indicator (e.g. Jorion et al. 2009). Detailed variable definitions are provided in Appendix 1.

Since we are interested in predicting discrete ratings probabilities, following prior literature (e.g. Blume et al. 1998, Jorion et al. 2009) we estimate equation (1) using ordered probit models.[8] To mitigate the impact of extreme observations all continuous variables are winsorized at the extreme percentiles.

Based on the approach of Hann et al. (2007) and Jorion et al. (2009) we estimate the explanatory power of equation (1) with reference to the pseudo-R^2 statistic, an overall measure of goodness of fit equal to one in the case of a perfect fit. We follow Ohlson (1980) and Jorion et al. (2009) and employ the McFadden (1974) pseudo-R^2 statistic.[9]

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[7] Blume et al. (1998) argue that although the relation between the latent variable for credit ratings and interest coverage is predicted to be positive, the effect should be non-linear. For example, a small change in interest coverage when interest coverage is high is expected to have a negligible effect on credit risk. Consequently, Blume et al. (1998) and Jorion et al. (2009) capture potential non-linear interest coverage effects by recoding interest coverage as four indicator variables, as described in Appendix 1.

[8] Our findings are robust to the employment of OLS as in Hann et al. (2007).

[9] Several alternative pseudo-R^2 measures have been defined for models with categorical response variables. However, the McFadden (1974) pseudo-R^2 is generally accepted as a reasonable measure of goodness of fit analogous to the OLS R^2 statistic, with values close to one (zero) indicating high (low) ability to explain categorical outcomes. The McFadden (1974) pseudo-R^2 is defined as 1- LL_M/LL_R, where LL_M is the log likelihood of the

3.2. *Comparing credit relevance*

As in prior research, we interpret differences in the model's explanatory power between two accounting regimes (or two time periods) as evidence of differences in credit relevance (Hann et al. 2007, Jorion et al. 2009). Specifically, for our primary test of whether the credit relevance of accounting numbers changes in the switch to IFRS from domestic accounting standards, we compare the pseudo-R^2 of equation (1) based on a constant sample of mandatory IFRS adopters for which credit ratings are available in both the pre-IFRS (2000-2004) and the post-IFRS (2005-2009) periods. We perform this comparison for the full IFRS sample and separately for IFRS firms with investment-grade and speculative-grade credit ratings. If IFRS financial statements have higher credit relevance than financial statements prepared under domestic accounting standards then we expect an increase in the explanatory power of the credit rating model from the pre-IFRS period to the post-IFRS period. In this design each IFRS firm serves as its own control, thereby mitigating the potential impact of changes in sample composition over time and allowing us to be more confident that observed changes in credit relevance are attributable to the switch from domestic accounting standards to IFRS.[10] We also predict that any increase in the model's explanatory power is more pronounced for speculative-grade issuers with higher default risk than for investment-grade issuers.

To address possible concerns that estimated changes in credit relevance could be driven by changes in the economic environment of IFRS adopters unrelated to the financial reporting

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estimated model and LL_R is the log likelihood of the restricted intercept-only model. See Hu et al. (2006) for further discussion.

[10] We note that if estimated changes in credit relevance are to be attributed to financial reporting changes, the methodology mapping economic fundamentals into credit ratings should be relatively stable. Indeed, credit rating agencies emphasize the consistency of their rating processes over time and across firms. In line with such claims Jorion et al. (2009) find no evidence suggesting that credit standards have tightened over time. The stability of ratings processes over time helps mitigate concerns that any observed credit relevance changes subsequent to the adoption of IFRS could be attributed to changes in rating practices rather than changes in financial reporting.

system, we also employ a matched-sample design where the IFRS sample is matched to a sample of US firms that are subject to the same credit rating process but report under US GAAP. Similarly to Barth et al. (2012), for each year over the 2000-2009 period we match each mandatory adopter to a US firm in the same credit rating category (i.e. investment/speculative), same industry sector and year and of similar size, measured by equity market value.[11] We then estimate comparative changes in the credit relevance of financial statement numbers under IFRS and US GAAP using a difference-in-differences design. If IFRS provide more informative accounting numbers (compared to domestic accounting standards) then we expect any increase in credit relevance to be greater for IFRS adopters than for the US control group. In robustness checks we demonstrate that results are insensitive to the matched sample design by repeating our comparative analysis using the full US population of firms with credit ratings.

3.3. *IFRS reconciliations analysis*

We establish a direct link between credit relevance changes and a firm-level measure of the impact of IFRS on accounting amounts, exploiting reconciliations of pre-adoption year comparative financial statements. For the majority of firms where first-time IFRS financial statements are for fiscal year end December 2005, the restated accounting numbers are for fiscal year end December 2004; for the remaining firms that adopt IFRS for the first time during 2006, reconciliations relate to the fiscal year ending during 2005.

[11] Ideally we would like to match on the same credit rating score rather than the same credit rating category. However, this is not possible due to the smaller pool of available US peers. But, we assess the sensitivity of our results to alternative matching procedures in Section 5.2. We group firms into 12 aggregate sector groups based on Campbell (1996) using the SIC industry classifications (WS07021). Sectors are defined as follows (WS industry numbers in parentheses): Petroleum (13 and 29), Consumer Durables (25, 30, 36, 37, 50, 55, 57, and 39), Basic Industry (10, 12, 14, 24, 26, 28, 33, and 8), Food and Tobacco (1, 20, 21, 54, and 2), Construction (15-17, 32, and 52), Capital Goods (34, 35 and 38), Transportation (40-42, 44, 45, and 47), Utilities (46, 48, and 49), Textiles and Trade (22, 23, 31, 51, 53, 56, and 59), Services (72, 73, 75, 80, 82, 89, 7, 76, 83, and 87), Leisure (27, 58, 70, 78, 79, and 91-99) Finance and Real Estate (60-69).

We perform two complementary tests using first-time IFRS reconciliations. First, we examine the pseudo-R^2 of equation (1) for sub-samples of mandatory adopters based on the degree to which IFRS affects the accounting variables in the credit rating model. Second, we focus on the year prior to IFRS adoption and investigate the relative explanatory power of equation (1), first using accounting items prepared under domestic standards and then using IFRS-restated accounting items; we execute this analysis for sub-sets with different levels of reconciliations.

We collect all firm-level restated accounting items from Worldscope and identify those due to first-time IFRS application if the indicator Restatement Reason (WS11559) is coded 4 (i.e. 'Accounts are restated due to a change in GAAP followed by the company') and the indicator Accounting Standards Followed (WS07536) is coded 23 (i.e. 'IFRS'). We estimate firm-specific IFRS reconciliations as (accounting item under domestic standards - IFRS restated accounting item) for each variable used in equation (1). We winsorize each reconciliation item at the extreme percentiles.

We define extreme reconciliations using the following procedure. For each of the six accounting variables in equation (1) we generate a binary indicator equal to one if the reconciliation is either in the top or the bottom quartile of the distribution.[12] We then add the six extreme reconciliation indicators and obtain a composite score, labelled *Total Extreme Reconciliations*, with a theoretical range from 0 (i.e. the firm reports no extreme reconciliations at all) to 6 (i.e. the firm reports extreme reconciliations for all six accounting variables). We classify a firm as having large (small) reconciliations if *Total Extreme Reconciliations* is greater

[12] Applying different cut-off points to identify extreme firm reconciliations, i.e. top and bottom 15 and 35 percent, does not alter our inferences. Similarly, using the absolute value of firm actual reconciliations yields consistent results.

than or equal to 4 (lower than 4).[13] We assume that large (small) reconciliations indicate higher (lower) de facto divergence between domestic accounting standards and IFRS.

We use the extreme reconciliations proxy to test whether IFRS have higher credit relevance as follows. First we test whether firms with small first-time reconciliations have higher estimated credit relevance than those with large reconciliations in the pre-IFRS period. Then we examine credit relevance in the pre-IFRS adoption year and test whether any increase in credit relevance in moving from domestic accounting standards to IFRS-restated numbers is higher for the large reconciliations sub-sample. Finally, we test whether any observed improvement in credit relevance between the pre- and post-IFRS periods is more pronounced for mandatory IFRS adopters with large reconciliations.

4. Sample and descriptive statistics

4.1. *Sample composition*

We compile our data by merging the S&P long-term issuer credit ratings database with Worldscope fundamentals data. We merge databases based on company name, the only firm identifier provided by S&P, employing a name-matching algorithm supplemented by manual checks. The S&P database covers 15,401 unique rated entities over the sample period 2000-2009 and our matching process yields an initial sample of 3,863 firms with Worldscope data.[14]

We identify the accounting standards used in each firm-year based on the Worldscope reporting standards code (WS07536) as applied by Daske et al. (2013). In defining the

[13] For example, a firm with *ROA* and *SIZE* extreme reconciliations obtains a *Total Extreme Reconciliations* score of two; in this case the *ROA* and the *SIZE* reconciliation (i.e. the difference between local GAAP and IFRS in *ROA* and *SIZE*, respectively) are below the 25th or above the 75th percentile of the respective reconciliation distribution.

[14] Our matched sample accounts for 25 percent of the S&P issuer universe over the period 2000-2009. However, the true matched proportion is higher after excluding non-corporate issuers (e.g. states, municipalities, etc.) and non-listed issuer entities (i.e. private firms or subsidiaries of public firms). Unfortunately, the S&P database does not allow us to identify such entities explicitly.

mandatory IFRS sample we then exclude: firms without necessary financial statement and credit rating data; firms from countries that do not mandate IFRS reporting in the sample period (e.g. Canada, Japan, and US) or from countries that did not mandate IFRS for first time in 2005 (e.g. Singapore, Israel, and New Zealand); voluntary IFRS adopters; firms that do not switch to IFRS (e.g. firms in mandated IFRS countries that do not prepare consolidated financial statements); firms that used US GAAP before IFRS adoption; and mandatory adopters without observations in both the pre-IFRS and the post-IFRS periods. Applying these criteria we obtain a final sample of 202 unique firms with credit ratings and reporting under IFRS from seventeen countries yielding a total of 1,664 firm-years.[15] We summarize the IFRS sample selection process in Table 1.

The sample of IFRS firms with credit ratings represents a relatively small proportion of the universe of all mandatory IFRS adopters. To provide some insights to the representativeness of our sample we compare sample firm characteristics to the Worldscope universe and the subset of mandatory IFRS adopters within the Worldscope universe. Un-tabulated results show that our sample firms are larger, more leveraged and more profitable than both the Worldscope universe and the broader set of mandatory IFRS adopters. These differences are unsurprising given that Worldscope (and in turn the subset of firms in countries where IFRS is mandated) includes a large number of smaller and younger firms which rely less on public debt financing and are therefore less likely to receive an S&P issuer credit rating (Denis and Mihov 2003). We also compare financial and credit rating data of US firms in the S&P-Worldscope intersection to those

[15] Our final sample is smaller compared to that of related prior studies (Ashbaugh-Skaife et al. 2006, Hann et al. 2007, Jorion et al. 2009). However, these papers focus exclusively on US firms and therefore obtain larger samples due to credit rating and financial data being obtained from the same database, i.e. Compustat. Similar to our study Wu and Zhang (2014) match data from the Moody's default risk database and Worldscope and obtain an international credit rating sample of comparable size to ours (i.e. 1,917 vs. 1,664 firm-year observations).

of US rated firms examined in prior studies (Ashbaugh-Skaife et al. 2006, Jorion et al. 2009). In general, un-tabulated results show that there are no marked differences in firm characteristics, suggesting that our matching process is unlikely to introduce important biases to the analysis.

Table 2 presents the sample composition analyzed by credit rating (Panel A), country (Panel B) and industry sector (Panel C). As shown in Panel A, S&P long-term issuer credit ratings range from AAA to CC with rating BBB+ (CC) having the highest (lowest) proportion of total observations (19.89 and 0.12 percent, respectively). Further, the majority of firms (86.66 percent) are rated investment grade, i.e. BBB- or above. Panel B indicates that UK, Australia and France have the highest representation in the sample. We note that the low number of firms in several countries (e.g. Belgium, Denmark, Italy etc.) can be attributed to the small population of these countries provided by the S&P database. Our sample is fairly evenly allocated between the pre- and post-IFRS period with 56.43 and 43.67 percent of observations respectively in the pre-IFRS and the post-IFRS periods. Rating agencies often group firms into four major industry sectors; as reported in Panel C, the majority of sample firms are industrials (63.53 percent).

4.2. *Descriptive statistics*

Table 3 provides descriptive statistics of the variables used to estimate equation (1). We report results separately for the pre-IFRS period and the post-IFRS period. Panel A refers to the sample of mandatory IFRS adopters, while Panels B and C relate to the matched US sample and the US population, respectively. In the case of mandatory IFRS adopters, there are significant differences between the pre-IFRS period and the post-IFRS period for several accounting variables. For example, after IFRS adoption firms have, on average, higher interest coverage, higher profitability, lower total debt, higher total assets and lower capital intensity. The reported differences are consistent with IFRS having systematic effects on financial statement numbers used in the credit relevance model to capture economic fundamentals. We also note that the proportions of firms rated with investment (speculative) grade do not change significantly over the periods surrounding mandated IFRS adoption. The similarity in the distributions of ratings over sub-sample periods provides reassurance that the ratings process is relatively stable and is therefore unlikely to be a factor that could lead to differences in estimated credit relevance.[16]

5. Empirical results

In this section we present our empirical findings. First, we compare the explanatory power of the accounting-based credit rating model between the pre-IFRS period and the post-IFRS adoption period, using the overall IFRS and matched US samples, as well as the US population. Next, we assess the robustness of our primary findings in many ways. Then we examine credit relevance changes for sub-samples comprising mandatory IFRS adopters with investment-grade and speculative-grade ratings; and with small and large reconciliations at first-time IFRS application.

5.1. *Credit relevance before and after mandatory IFRS adoption*

Table 4 reports the difference-in-differences analysis comparing credit relevance between mandatory IFRS adopters and US firms before and after the mandatory IFRS adoption date. Panels A and B refer to the matched US sample and the US population of firms, respectively. The reported pseudo-R^2 statistics are in line with those documented in prior studies (e.g. Jorion et al. 2009). As shown, the pseudo-R^2 statistic for mandatory IFRS adopters is higher by 2.5

[16] Un-tabulated analysis reveals that there are no significant correlations between the independent variables, with the exception of the two leverage factors that, as expected, are highly correlated. Because of this we assess the sensitivity of our results to the exclusion of *LTD Leverage* and find similar results.

percentage points in the post-IFRS period compared to the pre-IFRS period (24.5 percent and 22.0 percent, respectively). This finding suggests that IFRS accounting numbers are more capable than accounting numbers prepared under domestic accounting standards of capturing the economic fundamentals explaining default probabilities, as reflected in analysts' credit ratings.

Table 4 Panel A shows that the pseudo-R^2 measure is higher by 0.9 percentage points for the US counterparts over the pre- to post-IFRS period, albeit this increase is smaller than that for the IFRS firms. After controlling for time trends in credit relevance captured in the US benchmark sample, we observe an increase of 1.6 percentage points in estimated credit relevance between the two groups of firms following mandatory IFRS adoption.[17] Empirical findings in Panel B are broadly consistent with those in Panel A; for example, while credit relevance for the population of US firms increases slightly between the pre-IFRS period and the post-IFRS period by 0.2 percentage points, this increase is lower than that reported for the IFRS sample. Collectively, these findings enhance our confidence that the observed improvement in credit relevance for the IFRS sample is likely attributed to the transition to the IFRS financial reporting regime.

As mentioned earlier, we are agnostic about the magnitude and change in values of the slope coefficients of the accounting-based factors. However, we present the estimation results of equation (1) in Appendix II. In general, the accounting variables have the expected signs; that is,

[17] To the best of our knowledge there is no parametric test of statistical significance for differences in goodness of fit statistics from models estimated on different samples. The absence of such tests in prior literature (Jorion et al. 2009) is consistent with this claim. It is possible to apply bootstrap techniques where the treatment effect is randomly assigned to produce simulated distributions of goodness of fit statistics. However, in this case as shown by Barth et al. (2012) it is important to control for country and industry fixed effects when using an international sample. Failure to do so would confound the simulated distribution of goodness of fit statistics with country and industry effects. As mentioned in footnote 6 our aim is to compare the relevance of accounting information in explaining credit ratings under two alternative financial reporting regimes; therefore, we focus our analysis on the model specification that excludes fixed effects and contains accounting variables only. We are able to test for statistical significance controlling for country and industry fixed effects as described in Section 5.2.

larger firms as well as firms with higher interest coverage, profitability and capital intensity and lower long-term leverage receive higher credit ratings. Also, we find that in the post-IFRS period the estimates of interest coverage (i.e. *IntCov2* and *IntCov3*) as well as *Size* become more positive and the estimate of *Loss* becomes more negative. These findings, although not directly comparable to prior work due to different research designs, are broadly consistent with the results of Wu and Zhang (2014); they document a significant post-adoption increase in the sensitivity of credit ratings to accounting numbers for mandatory IFRS adopters, but only in countries with strong rules of law (see their Table 5, columns 3 and 4). To examine further the impact of the legal environment we replicate our analysis reported in Table 4 after splitting the IFRS sample into two groups of countries conditioning on financial reporting enforcement based on the Brown et al. (2014) index.[18] Consistent with Wu and Zhang (2014) un-tabulated analysis reports that the increase in the pseudo-R^2 of the credit rating model from the pre-IFRS period to the post-IFRS period is evident primarily for IFRS adopters in countries where financial reporting compliance is higher. Overall, the results in Table 4 are consistent with IFRS financial statements being more successful than domestic accounting standards in capturing the economic fundamentals underpinning credit ratings.

5.2. *Robustness of basic test results*

We perform a number of additional tests to assess the robustness of the findings reported in Table 4. We tabulate selected analyses in Table 5. Note that we estimate sensitivity tests using as

[18] To focus explicitly on factors that affect how compliance with accounting standards was promoted around the time of IFRS adoption we use the index of financial reporting enforcement constructed by Brown et al. (2014). This index measures the degree of accounting enforcement activity by independent enforcement bodies and is constructed based on publicly available data provided by the International Federation of Accountants (IFAC), the World Bank and the national securities regulators. In our analysis we partition the IFRS sample using the country-level median value of the ENFORCE index for years 2002 or 2005 or 2008; the country-level median value of the average ENFORCE index for years 2002, 2005 and 2008; and the median value of the ENFORCE index based on all 1,664 observations.

benchmark both the US matched sample and US population, wherever applicable; inferences remain qualitatively unchanged across the two alternative control groups, but for brevity we tabulate findings only for the US matched sample.[19]

First, we employ a series of different IFRS sample definitions, as follows: (a) we focus only on IFRS adopting countries with relatively large numbers of observations (i.e. UK, Australia and France) to ensure that results are not driven by small countries; (b) we extend our sample to all mandatory IFRS adopters without requiring them to have credit rating and financial statement data in both the pre- and post-IFRS periods to address concerns of potential survivorship bias in our sample; (c) we exclude UK firms to ensure our findings are not attributed to the largest country in the sample; (d) we eliminate financial firms because of the specific structure of their financial statements and distinct reporting requirements; (e) we drop countries where voluntary adoption of IFRS was permitted prior to 2005 (i.e. Denmark, Finland, Germany and South Africa) to address potential selection bias concerns; and (f) we exclude countries that introduced a change from reactive review of financial statements to proactive review at the same time as mandatory IFRS adoption, to mitigate concerns that the reported increase in credit relevance results from enforcement reforms (Christensen et al. 2013).[20] In all these tests the observed increased credit relevance persists.

Second, we employ the populations of Canadian and Japanese firms as alternative benchmark samples (see Panel A).[21] Similarly, we adopt alternative matching procedures by

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[19] Empirical findings for all sensitivity tests are available from the authors on request.

[20] These countries include Finland, Germany, Netherlands, Norway and UK. However, we acknowledge that credit ratings are relatively sticky and therefore provide a potentially less appropriate setting for testing the Christensen et al. (2013) hypothesis. Accordingly, we cannot entirely rule out the possibility that the observed credit relevance effects are the joint outcome of mandatory IFRS adoption and contemporaneous regulatory changes.

[21] It is not feasible to follow a matched-sample process as in the case of US; such an analysis would reduce the IFRS sample due to the lower number of total observations of the Canadian and Japanese population with all the required financial and credit rating data (i.e. 803 and 1,618 firm-years, respectively).

matching each IFRS firm-year with a US peer in the same year having similar predicted credit rating probability and size; and by matching each IFRS observation with a random US observation in the same industry and year.[22] In all cases, empirical findings are qualitatively identical to those reported in Table 4.

Third, in line with prior literature we estimate alternative versions of the credit rating model, including: (a) *Operating Margin* and *Return on Equity* (*ROE*) as alternative profitability measures (Jorion et al. 2009); (b) *Current Ratio* and *Operating Cash Flow Ratio* as additional explanatory variables capturing liquidity effects (Jorion et al. 2009); (c) interest coverage ratio (*IntCov*) as a linear term in place of the four interest coverage indicators (Ashbaugh-Skaife et al. 2006, Cheng and Subramanyam 2008, Wu and Zhang 2014); and d) market-based factors, namely *Equity Beta, Residual Volatility* and *Returns Variability* in addition to the accounting-based variables (Jorion et al. 2009) (see Panel B).[23] Again, results remain qualitatively unchanged.

Fourth, similar to Barth et al. (2012) we repeat our empirical analysis after including country and industry fixed effects to control for any systematic differences in credit ratings across countries and industries that could affect credit relevance comparisons. As expected, the inclusion of these fixed effects increases the statistical performance of the credit rating model and estimated pseudo-R^2 statistics are higher than those reported in Table 4 in both the pre- and post-IFRS periods. In this specification the credit relevance for the IFRS sample increases by 7.9

[22] In the first approach we estimate predicted credit rating probabilities based on our model described in equation (1) and after including industry dummies whereas in the second approach we select a random sample of US counterparts irrespective of their size and calculate the average difference in pseudo-R^2 over the pre- to post-IFRS period based on 100 random samples.

[23] *Equity Beta* is estimated from the market model using daily stock returns in each calendar year. The beta estimates are controlled for nonsynchronous trading effects using the Dimson (1979) procedure with one leading and lagging value of the market return (market return is based on MSCI World Index). *Residual Volatility* is the standard error of the market model. *Returns Variability* is computed as the annual standard deviation of monthly stock returns. Data is obtained from Datastream.

percentage points after the adoption while the equivalent change for the matched US sample is 0.2 percentage points.[24]

Fifth, we assess the robustness of our inferences to using two alternative goodness of fit measures for credit relevance, namely the McKelvey and Zavoina (1975) pseudo-R^2 and the Rank Probability Score (see Panels C and D, respectively).[25] Using these alternative criteria, base line inferences remain unchanged. For example, the overall prediction accuracy of the credit rating model based on the Rank Probability Score increases by 2.7 percentage points for mandatory IFRS adopters following the adoption but only by 0.5 percentage points for the US matched firms over the same period.

Sixth, we restrict our sample period to 2000-2007 to control for the potential effects of the global financial crisis (see Panel E). Then we employ an ordered probit model after equally weighting each firm in estimation (i.e. using firm averages for the pre- and post-IFRS periods instead of weighting each firm by the number of firm-years in a sub-sample); after averaging accounting variables over a 2-year and 3-year period (Jorion et al. 2009); and after measuring credit ratings three months following fiscal year-end (see Panel F). In all these tests we find results consistent with our main findings in Table 4.

[24] As discussed earlier in footnote 17, the inclusion of fixed effects allows us to assess the statistical significance of the difference in the pseudo-R^2 statistic between the IFRS and US samples in the post-IFRS period using bootstrap techniques. Specifically, following Barth et al. (2012) we randomize between treated and benchmark US firms around IFRS adoption to obtain bootstrap treatment and control samples and then calculate a difference in the pseudo-R^2 statistics across the two samples. Repeating the above procedure 1,000 times, we obtain the empirical distribution of the difference in pseudo-R^2 statistics. Results indicate that this difference is statistically significant (p-value=0.029).

[25] Compared to the McFadden pseudo-R^2 the McKelvey and Zavoina (1975) pseudo-R^2 has the disadvantage that it does not indicate the level of improvement in goodness of fit of the full model relative to the 'naive' intercept-only model. The Rank Probability Score (RPS) measures the accuracy of probability estimates when the response variable has more than two categories. In general, prediction accuracy increases as the model fit improves (BarNiv and McDonald 1999). The RPS score is zero for a perfect forecast and positive otherwise; lower values, therefore, imply higher prediction accuracy. We multiply differences in RPS by -1 for easier interpretation of results.

Finally, we perform a series of 'placebo tests' by shifting the IFRS adoption date two years backwards (i.e. to 2003); by randomly assigning each firm-year to the pre- and post-IFRS periods; and by randomly shifting IFRS adoption one, two or three years backwards for each firm. In all these tests the explanatory power of the credit rating model for mandatory adopters does not increase between the pre-placebo date and the post-placebo date periods; instead it either remains unchanged or decreases slightly.

Overall, our inferences concerning the incremental credit relevance of IFRS financial statement numbers appear insensitive to a wide range of research design choices.

5.3. *Changes in credit relevance of IFRS: investment-grade versus speculative-grade firms*

We now continue our analysis by examining changes in credit relevance for investment-grade and speculative-grade mandatory IFRS adopters separately. Table 6 reports the findings. As shown, for both investment-rated and speculative-rated issuers accounting numbers prepared under IFRS are more successful in capturing the economic fundamentals underpinning credit ratings than those prepared under domestic accounting standards. However, consistent with predictions the increase in credit relevance is more than twice as high for the speculative-grade sub-sample (10.0 percentage points) compared to the investment-grade sub-sample (4.9 percentage points).

Un-tabulated analysis comparing investment-grade and speculative-grade firms across the IFRS and US GAAP samples reveals a larger increase in credit relevance in the post-IFRS period for both IFRS sub-sets relative to their respective US GAAP peers. Also, empirical findings remain qualitatively unchanged when we repeat the analysis after constraining slope coefficient estimates in the ordered probit models to be equal across models for investment-grade and speculative-grade IFRS issuers. This ensures that changes in estimated credit relevance are not driven by differences in model calibration arising from estimation in different sub-samples partitioned on the dependent variable. In this case, the explanatory power of the credit-relevant accounting items increases for both groups of IFRS firms in the post-IFRS period, but the increase is much higher for those with a speculative credit rating; the difference between the two estimates is 20.7 percentage points.

In sum, our empirical findings suggest stronger links between credit ratings and IFRS accounting numbers for speculative-grade firms. This finding is consistent with prior studies indicating stronger association between bond values and accounting information (e.g. De Franco et al. 2009, Givoly et al. 2013) for lower credit quality issuers. Overall our results suggest that the documented increase in credit relevance after IFRS adoption is more likely associated with IFRS per se than with other omitted correlated factors.

5.4. *Changes in credit relevance of IFRS: small versus large reconciliations*

Next, we discuss sub-sample analysis based on the magnitude of the first-time IFRS adoption reconciliations. Table 7 reports the results of this analysis. Panels A and B provide descriptive statistics while Panels C, D and E document the regression analysis findings. Panel A presents the distribution of *Total Extreme Reconciliations*. We classify 44.06 percent (55.94 percent) of the IFRS sample as reporting large (small) overall IFRS impact on credit relevant accounting numbers. Panel B reports the descriptive statistics for the absolute values of accounting item reconciliations across the small and large reconciliation sub-samples. Our classification shows that the economic significance of restatements of accounting variables as a result of switching to IFRS can be quite high. For example, for the small reconciliation group, the mean (median) absolute value of the change in interest coverage is 1.35 (0.495) times, while for the large reconciliation group the change is 1.967 (1.124) times. Un-tabulated analysis shows that our composite extreme reconciliations measure captures firm-level information beyond country or industry effects. For example, 34 percent (66 percent) of the UK sample is classified as having small (large) reconciliations; while 55 percent (45 percent) of utilities firms are assigned to the small (large) reconciliation sub-sample.

In Panel C we repeat the credit relevance analysis based on equation (1) after partitioning firms into small and large reconciliation sub-samples in both the pre- and post-IFRS periods. Prior to the implementation of IFRS the pseudo-R^2 statistic of the credit rating model is much higher for IFRS adopters with small reconciliations; the difference in estimated credit relevance between the small and large reconciliation sub-sets is 12.8 percentage points. This result suggests that credit rating analysts understand the deficiencies of domestic accounting standards in capturing economic fundamentals relevant to credit ratings decisions. It also suggests that they are able to anticipate some of the potential effects of IFRS on financial reporting. We also see from Panel C that the overall increase in credit relevance for IFRS adopters depends on the magnitude of first-time reconciliations, and hence on the impact of IFRS on credit relevant accounting numbers; the increase in the pseudo-R^2 of the credit rating model from the pre-IFRS period to the post-IFRS period is evident only for IFRS adopters with large reconciliations, the magnitude of the increase being 4.9 percentage points. This finding is similar in spirit to results in Horton et al. (2013), who find a higher increase in the accuracy of equity analysts' earnings forecasts for mandatory IFRS adopters with larger reconciliations.

Panel D reports the comparative credit relevance of domestic standards relative to IFRS-restated accounting amounts for the year prior to IFRS adoption. Again, the credit relevance of the IFRS-restated accounting numbers depends strongly on the magnitude of the reconciliations; the pseudo-R^2 of the IFRS-based credit rating model is higher than that of the local GAAP-based model but only for mandatory IFRS adopters with large reconciliations (credit relevance increases by 5.6 percentage points). In Panel E we repeat the above analysis for each reconciliation item separately, and we summarise the differences in the pseudo-R^2 statistics between the IFRS-based and the domestic accounting standards-based models for small and large reconciliations. As shown, in all cases (with the exception of *LTD Leverage*) the credit relevance of the IFRS-restated accounting numbers is higher than that of the equivalent local GAAP numbers, but only for issuers with large reconciliations. Consistent with Panel C, these finding suggests that credit rating analysts understand the differences between domestic accounting standards and IFRS and that IFRS numbers better reflect economic fundamentals.

Overall, empirical findings in Table 7 support our expectation that the positive impact of the mandatory transition to IFRS on the credit relevance of accounting numbers is associated primarily with firms where there is higher de facto divergence between reporting under domestic accounting standards and under IFRS. Consequently, these findings help mitigate concerns that the observed changes in credit relevance are driven by other concurrent changes excluded from the analysis.

6. Conclusions

In this study we examine changes in the credit relevance of accounting information at the time of mandatory IFRS adoption. We define credit relevance as the extent to which accounting numbers are associated with default probabilities. We employ S&P issuer credit ratings as a surrogate for default risk and estimate the relation between credit ratings and financial statement numbers reported by mandatory IFRS issuers under domestic accounting standards in the pre-IFRS period and under IFRS in the post-IFRS period. Our credit relevance metric is based on the explanatory power of the model, as captured by the pseudo-R^2 statistic.

Using a constant sample of mandatory IFRS adopters from seventeen countries over the period 2000-2009, we document a number of findings that are new to the literature. First, we document an increase in the explanatory power of the credit rating model after IFRS adoption for the full sample of mandatory adopters. Second, the observed credit relevance improvement is greater than that reported for a matched sample of US firms over the same period. We interpret our empirical findings as indicating that IFRS provide more reliable and informative financial statements to creditors than financial statements prepared under domestic accounting standards.

In subsequent tests we demonstrate that improvements in the credit relevance of IFRS financial statements are more pronounced in specific sub-samples for which stronger effects are predicted; namely, for mandatory IFRS adopters with speculative credit ratings rather than investment credit ratings, where the demand for accounting information is expected to be higher; and for IFRS adopters with large first-time reconciliations, where the impact of IFRS on credit-relevant accounting numbers is greater. These findings improve confidence that the changes in credit relevance we observe for the full sample are related to the financial reporting changes resulting from the switch from domestic accounting standards to IFRS, rather than to other un-modelled factors.

Two findings in particular point to credit rating analysts being effective in processing financial statement information and understanding differences between accounting standards regimes. First, prior to IFRS adoption the ability of accounting numbers to determine credit ratings is higher for IFRS issuers who subsequently report small first-time reconciliations.

Second, IFRS restatements of accounting numbers relating to the pre-IFRS adoption year have higher explanatory power for contemporaneous credit ratings than the equivalent accounting numbers reported under domestic accounting standards, but only for IFRS adopters reporting large first-time reconciliations, even though they are not known at the time.

Our results are subject to at least two caveats. First, they are based on a selected sample of firms that are rated by one of the major rating agencies. Results might not generalize to other rating agencies; or to firms that do not have credit ratings. Second, we assume that credit ratings capture fundamental differences in default risk across firms. To the extent that credit ratings are incomplete measures of default risk, our results could understate the credit relevance of IFRS financial statements. Nevertheless, subject to these caveats, our study documents that mandatory IFRS adoption is associated with improved informativeness of financial statements from the perspective of creditors.

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APPENDIX 1
Variable definitions

Rating	Rating score assigned to Standard & Poor's long-term issuer credit rating at the end of fiscal year, converted into numerical values from 1 (CC) to 8 (AAA)
InvGrade	Binary variable that equals 1 if a firm's credit rating is investment grade (i.e. BBB- or higher), and 0 if rating is speculative grade
IntCov	Interest coverage ratio measured as operating income before depreciation (WS18155) minus depreciation (WS01151) deflated by interest expense (WS01251). The variable is treated in a non-linear fashion. After setting *IntCov* to 0 for negative values and to 100 for values above 100, four variables are constructed as described below
*IntCov*1	Variable equals *IntCov* if $0 \leq IntCov < 5$, and 5 otherwise
*IntCov*2	Variable equals 0 if *IntCov*< 5, equals (*IntCov*-5) if $5 \leq IntCov < 10$, and 5 otherwise
*IntCov*3	Variable equals 0 if *IntCov*< 10, equals (*IntCov*-10) if $10 \leq IntCov < 20$, and 10 otherwise
*IntCov*4	Variable equals 0 if *IntCov*< 20, and (*IntCov*-20) otherwise
ROA	Net income before extraordinary items (WS01551) deflated by total assets (WS02999)
LTD Leverage	Long-term debt leverage measured as a ratio of long-term debt (WS03251) to total assets (WS02999)
TD Leverage	Total debt leverage measured as a ratio of total debt (WS03255) to total assets (WS02999)
Size	Natural log of total assets in USD (WS07230)
CI	Capital intensity measured as a ratio of net property, plant and equipment (WS02501) to total assets (WS02999)
Loss	Binary variable that equals 1 if net income before extraordinary items (WS01551) is negative in the current and prior fiscal year, and 0 otherwise
Operating Margin	Operating income before depreciation (WS18155) deflated by sales (WS01001)
ROE	Net income before extraordinary items (WS01551) deflated by book value of equity (WS03501)
Current Ratio	Current assets (WS02201) deflated by current liabilities (WS03101)
Operating Cash Flow	Net income bottom-line (WS01651) plus depreciation (WS01151) minus change in current assets (WS02201) plus change in current liabilities (WS03101) deflated by total debt (WS03255)
Market Capitalisation	Market value in USD (WS07210)
Equity Beta	Estimated from the market model using daily stock returns in each calendar year. The beta estimates are controlled for nonsynchronous trading effects using the Dimson (1979) procedure with one leading and lagging value of the market return (market return is based on MSCI World Index)
Residual Volatility	The standard error of residuals from the market model
Returns Variability	Annual standard deviation of monthly stock returns

This table provides details on the definition of all variables. Worldscope item codes are in parentheses.

APPENDIX 2
Estimation results of the credit rating model

Independent Variables	**Pre-IFRS**	**Post-IFRS**
IntCov1	0.085*	0.055
	(0.074)	(0.390)
IntCov2	0.098**	0.116***
	(0.036)	(0.009)
IntCov3	-0.039	0.064**
	(0.210)	(0.017)
IntCov4	0.017***	0.009
	(0.004)	(0.123)
ROA	3.085***	0.257
	(0.003)	(0.782)
LTD Leverage	-3.063***	-1.614*
	(0.002)	(0.094)
TD Leverage	1.660**	1.667
	(0.049)	(0.100)
Size	0.499***	0.603***
	(0.000)	(0.000)
CI	0.862***	0.707**
	(0.004)	(0.023)
Loss	-0.721***	-1.007***
	(0.001)	(0.002)
No. of observations	939	725
Pseudo-R^2 (McFadden)	0.220	0.245

This table reports coefficient estimates of the following model:

Rating = *f* (*IntCov*1, *IntCov*2, *IntCov*3, *IntCov*4, *ROA*, *LTD Leverage*, *TD Leverage*, *Size*, *CI*, *Loss*)

Total sample contains 1,664 firm-years for 202 unique mandatory IFRS adopters with observations in both the pre- and post-IFRS adoption period during 2000-2009. Models are estimated using the ordered probit regression, where *Rating* is an ordered dependent variable on a scale from 1 to 8. Other variable definitions are provided in Appendix 1.

All continuous variables are winsorized at the 1st and 99th percentiles. In parentheses we report p-values based on firm clusters and heteroskedasticity-corrected standard errors. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively (two-tailed test).

TABLE 1
Sample formation

	Firms	Firm-years
S&P database (2000 - 2009)	15,401	-
WS database (2000 - 2009)	45,440	-
Matched firms	3,863	-
Less firms with missing financial data	(311)	-
Matched firms with required financial data	3,552	26,869
Less firms from countries that do not mandate IFRS (either at all or in 2005)	(2,897)	(22,146)
Matched firms with required financial data and from countries that mandate IFRS in 2005	655	4,723
Less firms/observations with missing credit rating data	(23)	(1,095)
Matched firms with required financial and credit rating data and from countries that mandate IFRS in 2005	632	3,628
Less voluntary IFRS adopters	(160)	(935)
Less firms not switching to IFRS	(119)	(550)
Less firms using US GAAP	(21)	(107)
Mandatory IFRS adopters	332	2,036
Less mandatory IFRS adopters without observations in both periods	(130)	(372)
Final IFRS sample	**202**	**1,664**

TABLE 2
Sample composition

Panel A: By credit rating

S&P Issuer Credit Rating	Firm-years	%	Rating	InvGrade
AAA	9	0.54	8	Investment
AA+	20	1.20	7	Investment
AA	34	2.04	7	Investment
AA-	107	6.43	7	Investment
A+	134	8.05	6	Investment
A	162	9.74	6	Investment
A-	257	15.44	6	Investment
BBB+	331	19.89	5	Investment
BBB	251	15.08	5	Investment
BBB-	137	8.23	5	Investment
BB+	69	4.15	4	Speculative
BB	48	2.88	4	Speculative
BB-	47	2.82	4	Speculative
B+	20	1.20	3	Speculative
B	8	0.48	3	Speculative
B-	16	0.96	3	Speculative
CCC+	4	0.24	2	Speculative
CCC	8	0.48	2	Speculative
CC	2	0.12	1	Speculative
Total	1,664	100		

Panel B: By country

				Pre-IFRS	Post-IFRS
Country	**Firm-years**	**%**	**Firms**	**Firm-years**	**Firm-years**
Australia	338	20.31	40	193	145
Belgium	13	0.78	2	5	8
Denmark	10	0.60	1	6	4
Finland	17	1.02	2	9	8
France	256	15.38	31	145	111
Germany	39	2.34	5	19	20
Ireland	23	1.38	3	12	11
Italy	4	0.24	1	1	3
Netherlands	109	6.55	13	68	41
Norway	29	1.74	4	14	15
Philippines	26	1.56	4	11	15
Poland	7	0.42	1	4	3
Portugal	34	2.04	4	18	16
South Africa	13	0.78	2	5	8
Spain	102	6.13	12	58	44
Sweden	110	6.61	12	65	45
UK	534	32.09	65	306	228
Total	1,664	100	202	939	725

Panel C: By industry sector

Industry Sector	Firm-years	%	Firms	Pre-IFRS Firm-years	Post-IFRS Firm-years
Industrials	1,039	63.53	120	608	431
Transport	88	4.90	11	49	39
Utilities	350	21.16	42	194	156
Financials	187	10.41	29	88	99
Total	1,664	100	202	939	725

Total sample contains 1,664 firm-years for 202 unique mandatory IFRS adopters with observations in both the pre- and post-IFRS adoption period during 2000-2009. Panel A shows how ratings are grouped into eight categories to generate the dependent variable *Rating*. We also split ratings into investment grade and speculative grade (*InvGrade*). Panel B reports composition of the sample by country and shows number of observations in the pre- and post-IFRS adoption period. Panel C reports composition of the sample by industry sector and reports number of observations in the pre- and post-IFRS adoption period.

TABLE 3
Descriptive statistics

Panel A: IFRS firms

	Pre-IFRS (N=939)					Post-IFRS (N=725)					Diff. in mean
	Mean	**SD**	**P25**	**Median**	**P75**	**Mean**	**SD**	**P25**	**Median**	**P75**	***p*-value**
IntCov	6.748	13.670	2.603	4.091	6.931	9.575	18.234	3.286	5.122	8.459	0.000
IntCov1	3.646	1.488	2.603	4.091	5.000	4.067	1.313	3.286	5.000	5.000	-
IntCov2	1.129	1.799	0.000	0.000	1.931	1.591	2.039	0.000	0.122	3.459	-
IntCov3	0.640	2.147	0.000	0.000	0.000	1.176	2.898	0.000	0.000	0.000	-
IntCov4	1.129	8.509	0.000	0.000	0.000	2.288	11.925	0.000	0.000	0.000	-
ROA	0.035	0.064	0.017	0.038	0.063	0.057	0.063	0.026	0.053	0.088	0.000
LTD Leverage	0.268	0.150	0.164	0.252	0.342	0.262	0.159	0.154	0.229	0.346	0.425
TD Leverage	0.347	0.157	0.236	0.341	0.433	0.331	0.167	0.211	0.307	0.430	0.038
Size	15.885	1.384	14.928	15.733	16.745	16.378	1.481	15.414	16.289	17.267	0.000
CI	0.393	0.259	0.179	0.360	0.600	0.360	0.268	0.130	0.308	0.560	0.010
Loss	0.068	0.252	0.000	0.000	0.000	0.036	0.186	0.000	0.000	0.000	0.004
Rating	5.420	0.987	5.000	5.000	6.000	5.292	0.922	5.000	5.000	6.000	0.007
InvGrade	0.880	0.326	1.000	1.000	1.000	0.850	0.358	1.000	1.000	1.000	0.074

Panel B: Matched US firms

	Pre-IFRS (N=939)					Post-IFRS (N=725)					Diff. in mean
	Mean	**SD**	**P25**	**Median**	**P75**	**Mean**	**SD**	**P25**	**Median**	**P75**	***p*-value**
IntCov	8.829	9.999	3.486	5.522	9.849	9.801	11.700	3.513	5.860	11.070	0.068
IntCov1	4.185	1.178	3.486	5.000	5.000	4.157	1.304	3.513	5.000	5.000	-
IntCov2	1.818	2.137	0.000	0.522	4.849	2.008	2.183	0.000	0.860	5.000	-
IntCov3	1.477	3.196	0.000	0.000	0.000	1.767	3.441	0.000	0.000	1.070	-
IntCov4	1.349	5.935	0.000	0.000	0.000	1.870	7.512	0.000	0.000	0.000	-
ROA	0.050	0.051	0.025	0.044	0.074	0.051	0.061	0.026	0.048	0.083	0.493
LTD Leverage	0.283	0.151	0.180	0.264	0.368	0.286	0.169	0.166	0.264	0.364	0.676
TD Leverage	0.330	0.156	0.229	0.317	0.416	0.333	0.172	0.210	0.310	0.416	0.744
Size	15.638	1.331	14.647	15.541	16.624	16.089	1.276	15.132	16.078	17.068	0.000
CI	0.408	0.254	0.193	0.371	0.603	0.401	0.274	0.166	0.338	0.634	0.620
Loss	0.045	0.207	0.000	0.000	0.000	0.039	0.193	0.000	0.000	0.000	0.539
Rating	5.279	0.911	5.000	5.000	6.000	5.206	0.901	5.000	5.000	6.000	0.101
InvGrade	0.880	0.326	1.000	1.000	1.000	0.850	0.358	1.000	1.000	1.000	0.074

Panel C: US population

	Pre-IFRS (N=5,924)					Post-IFRS (N=4,254)					Diff. in mean
	Mean	**SD**	**P25**	**Median**	**P75**	**Mean**	**SD**	**P25**	**Median**	**P75**	***p*-value**
IntCov	7.325	11.848	2.279	3.952	7.361	9.075	13.939	2.553	4.699	9.666	**0.000**
IntCov1	3.523	1.576	2.279	3.952	5.000	3.721	1.580	2.553	4.699	5.000	-
IntCov2	1.278	1.968	0.000	0.000	2.361	1.684	2.151	0.000	0.000	4.666	-
IntCov3	1.072	2.829	0.000	0.000	0.000	1.566	3.293	0.000	0.000	0.000	-
IntCov4	1.674	9.006	0.000	0.000	0.000	2.426	11.013	0.000	0.000	0.000	-
ROA	0.021	0.095	0.005	0.032	0.060	0.020	0.115	0.008	0.036	0.070	0.835
LTD Leverage	0.329	0.209	0.188	0.299	0.431	0.306	0.211	0.157	0.269	0.411	0.000
TD Leverage	0.380	0.215	0.238	0.350	0.484	0.351	0.221	0.200	0.317	0.461	0.000
Size	14.924	1.406	13.893	14.752	15.881	15.277	1.447	14.276	15.153	16.225	0.000
CI	0.380	0.263	0.159	0.329	0.586	0.347	0.271	0.115	0.279	0.557	0.000
Loss	0.147	0.354	0.000	0.000	0.000	0.119	0.324	0.000	0.000	0.000	0.000
Rating	4.569	1.212	4.000	5.000	5.000	4.466	1.182	4.000	5.000	5.000	0.000
InvGrade	0.536	0.499	0.000	1.000	1.000	0.505	0.500	0.000	1.000	1.000	0.002

Total sample contains 1,664 firm-years for 202 unique mandatory IFRS adopters with observations in both the pre- and post-IFRS adoption period during 2000-2009. Panels A, B and C report descriptive statistics for mandatory IFRS adopters, matched and all US firms, respectively, for the pre- and post-IFRS adoption period separately and the test of the difference in means. We report exact levels of significance of a two-sided test. For each year over the 2000-2009 period we match each mandatory adopter to a US firm in the same credit rating category (i.e. investment/speculative), same industry sector and year and of similar size, measured by equity market value. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix 1.

TABLE 4
Credit relevance before and after mandatory IFRS adoption
IFRS *vs*. US

Panel A: IFRS *vs.* matched US sample

Sample	Pre-IFRS (a)	Post-IFRS (b)	(b)-(a)
IFRS firms (i)	0.220 (N=939)	0.245 (N=725)	0.025
US firms (ii)	0.240 (N=939)	0.249 (N=725)	0.009
(i)-(ii)	-0.020	-0.004	0.016

Panel B: IFRS *vs*. US population

Sample	Pre-IFRS (a)	Post-IFRS (b)	(b)-(a)
IFRS firms (i)	0.220 (N=939)	0.245 (N=725)	0.025
US firms (ii)	0.263 (N=5,924)	0.265 (N=4,254)	0.002
(i)-(ii)	-0.043	-0.020	0.023

This table reports McFadden's pseudo-R^2 as the credit relevance metric of estimated models. Total sample contains 1,664 firm-years for 202 unique mandatory IFRS adopters with observations in both the pre- and post-IFRS adoption period during 2000-2009. For each year over the 2000-2009 period we match each mandatory adopter to a US firm in the same credit rating category (i.e. investment/speculative), same industry sector and year and of similar size, measured by equity market value.

All models are estimated using the ordered probit regression, where *Rating* is an ordered dependent variable on a scale from 1 to 8. Other variable definitions are provided in Appendix 1. Models are estimated separately for the pre- and post-IFRS adoption period and are of the form:

Rating = *f* (*IntCov*1, *IntCov*2, *IntCov*3, *IntCov*4, *ROA*, *LTD Leverage*, *TD Leverage*, *Size*, *CI*, *Loss*)

All continuous variables are winsorized at the 1st and 99th percentiles. All models are estimated with White standard errors adjusted to account for correlation within firm clusters.

TABLE 5
Credit relevance before and after mandatory IFRS adoption
Selected robustness analyses

Panel A: Employ the population of Canadian and Japanese firms as alternative benchmark samples

Sample	**Pre-IFRS (a)**	**Post-IFRS (b)**	**(b)-(a)**
IFRS firms (i)	0.220 (N=939)	0.245 (N=725)	0.025
Canadian firms (ii)	0.301 (N=451)	0.291 (N=352)	-0.010
(i)-(ii)	-0.081	-0.046	0.035
Japanese firms (iii)	0.196 (N=977)	0.133 (N=641)	-0.063
(i)-(iii)	0.024	0.112	0.088

Panel B: Include market-based variables

Sample	**Pre-IFRS (a)**	**Post-IFRS (b)**	**(b)-(a)**
IFRS (i)	0.266 (N=893)	0.299 (N=621)	0.033
US matched (ii)	0.294 (N=893)	0.281 (N=621)	-0.013
(i)-(ii)	-0.028	0.018	0.046

Panel C: Estimate the McKelvey and Zavoina pseudo-R^2

Sample	**Pre-IFRS (a)**	**Post-IFRS (b)**	**(b)-(a)**
IFRS firms (i)	0.500 (N=939)	0.529 (N=725)	0.029
US firms (ii)	0.521 (N=939)	0.530 (N=725)	0.009
(i)-(ii)	-0.021	-0.001	0.020

Panel D: Estimate the Rank Probability Score

Sample	**Pre-IFRS (a)**	**Post-IFRS (b)**	**(b)-(a)**
IFRS firms (i)	0.353 (N=939)	0.326 (N=725)	0.027
US firms (ii)	0.320 (N=939)	0.315 (N=725)	0.005
(i)-(ii)	-0.033	-0.011	0.022

Panel E: Restrict sample period to 2000-2007

Sample	**Pre-IFRS (a)**	**Post-IFRS (b)**	**(b)-(a)**
IFRS firms (i)	0.220	0.256	0.036
	(N=939)	(N=505)	
US firms (ii)	0.240	0.243	0.003
	(N=939)	(N=505)	
(i)-(ii)	-0.020	0.013	0.033

Panel F: Measure credit ratings three months after fiscal year-end

Sample	**Pre-IFRS (a)**	**Post-IFRS (b)**	**(b)-(a)**
IFRS firms (i)	0.233	0.247	0.014
	(N=939)	(N=725)	
US firms (ii)	0.243	0.251	0.008
	(N=939)	(N=725)	
(i)-(ii)	-0.010	-0.004	0.006

This table presents selected analyses assessing the robustness of findings reported in Table 4. For each year over the 2000-2009 period we match each mandatory adopter to a US firm in the same credit rating category (i.e. investment/speculative), same industry sector and year and of similar size, measured by equity market value.

All models are estimated using the ordered probit regression, where *Rating* is an ordered dependent variable on a scale from 1 to 8. Other variable definitions are provided in Appendix 1. Models are estimated separately for the pre- and post-IFRS adoption period and are of the form:

Rating = *f* (*IntCov*1, *IntCov*2, *IntCov*3, *IntCov*4, *ROA*, *LTD Leverage*, *TD Leverage*, *Size*, *CI*, *Loss*)

All continuous variables are winsorized at the 1st and 99th percentiles. All models are estimated with White standard errors adjusted to account for correlation within firm clusters.

In Panel B we include market-based variables, namely *Equity Beta*, *Residual Volatility* and *Returns Variability*. In Panels C and D, we employ two alternative goodness of fit measures of credit relevance, namely the McKelvey and Zavoina pseudo-$R^2$and the Rank Probability Score (RPS), respectively. The RPS measures the accuracy of probability estimates when the response variable has more than two categories; lower values imply higher prediction accuracy. For easier interpretation of results, we multiple differences in RPS by -1.

TABLE 6
Credit relevance before and after mandatory IFRS adoption
Investment-grade *vs.* speculative-grade firms

Sample	**Pre-IFRS (a)**	**Post-IFRS (b)**	**(b)-(a)**
Investment-grade (i)	0.181 (N=826)	0.230 (N=616)	0.049
Speculative-grade (ii)	0.208 (N=113)	0.308 (N=109)	0.100
(ii)-(i)	0.027	0.078	0.051

This table reports McFadden's pseudo-R^2 as the credit relevance metric of estimated models. Total sample contains 1,664 firm-years for 202 unique mandatory IFRS adopters with observations in both the pre- and post-IFRS adoption period during 2000-2009. Investment grade firms are rated BBB- or above.

All models are estimated using the ordered probit regression, where *Rating* is an ordered dependent variable on a scale from 1 to 8. Other variable definitions are provided in Appendix 1. Models are estimated separately for the pre- and post-IFRS adoption period and are of the form:

Rating = *f* (*IntCov*1, *IntCov*2, *IntCov*3, *IntCov*4, *ROA*, *LTD Leverage*, *TD Leverage*, *Size*, *CI*, *Loss*)

All continuous variables are winsorized at the 1st and 99th percentiles. All models are estimated with White standard errors adjusted to account for correlation within firm clusters.

TABLE 7
Credit relevance at the time of mandatory IFRS adoption
Small *vs*. large first-time IFRS reconciliations

Panel A: Total extreme reconciliations

Range	No. observations (%)
0	16 (7.92)
1	32 (15.84)
2	37 (18.32)
3	28 (13.86)
4	40 (19.80)
5	32 (15.84)
6	17 (8.42)

Panel B: Descriptive statistics

	Small (N=113)			Large (N=89)		
	Mean	**Median**	**SD**	**Mean**	**Median**	**SD**
IntCov	1.350	0.495	2.440	1.967	1.124	2.823
ROA	0.012	0.006	0.018	0.022	0.011	0.026
LTD Leverage	0.009	0.004	0.017	0.032	0.023	0.029
TD Leverage	0.005	0.003	0.005	0.027	0.019	0.028
Size	0.015	0.013	0.012	0.079	0.068	0.072
CI	0.011	0.006	0.015	0.030	0.024	0.030

Panel C: Pre-IFRS *vs*. post-IFRS period

Sample	Pre-IFRS (a)	Post-IFRS (b)	(b)-(a)
Small reconciliations (i)	0.295	0.285	-0.010
	(N=501)	(N=394)	
Large reconciliations (ii)	0.167	0.216	0.049
	(N=438)	(N=331)	
(ii)-(i)	-0.128	-0.069	0.059

Panel D: Local GAAP *vs*. IFRS-restated accounting factors

Sample	Local GAAP (a)	IFRS-restated (b)	(b)-(a)
Small reconciliations (i)	0.296	0.291	-0.005
	(N=113)	(N=113)	
Large reconciliations (ii)	0.211	0.267	0.056
	(N=89)	(N=89)	
(ii)-(i)	-0.085	-0.024	0.061

Panel E: Local GAAP *vs.* IFRS-restated accounting factors for each reconciliation

Variables	**Small reconciliations (i)**	**Large reconciliations (ii)**	**(ii)-(i)**
IntCov	-0.002	0.030	0.032
ROA	-0.001	0.022	0.023
LTD Leverage	0.018	0.013	-0.005
TD Leverage	-0.004	0.034	0.038
Size	0.002	0.058	0.056
CI	-0.003	0.038	0.041

Total sample contains 1,664 firm-years for 202 unique mandatory IFRS adopters with observations in both the pre- and post-IFRS adoption period during 2000-2009. Firm-level reconciliations are measured as (Local GAAP accounting item - IFRS restated accounting item). Panel A describes the distribution of *Total Extreme Reconciliations*, which is a categorical variable equal to the sum of six binary indicators (one for each accounting factor used in the credit rating model); each indicator takes the value of 1 if the reconciliation is extreme, i.e. it is in the top or bottom 25 percent, and 0 otherwise. *Total Extreme Reconciliations* may range from 0 (i.e. the firm reports no extreme reconciliations at all) to 6 (i.e. the firm reports extreme reconciliations for all six accounting variables). We classify a firm as having large (small) reconciliations if *Total Extreme Reconciliations* is equal to or higher than 4 (lower than 4). Panel B reports descriptive statistics of the absolute values of accounting item reconciliations for small and large firm-level reconciliation sub-samples. All actual reconciliations are winsorized at the 1^{st} and 99^{th} percentiles.

Panels C, D and E report McFadden's pseudo-R^2 as the credit relevance metric of estimated models. In Panel C we estimate the credit rating model in the pre- and post-IFRS period separately. In Panel D we focus on the last year prior to IFRS adoption and run the credit rating model using local GAAP and IFRS-restated accounting variables separately. In Panel E we repeat the analysis reported in Panel D for each reconciliation separately and we present the difference in McFadden's pseudo-R^2 between IFRS-restated and Local GAAP for small (i) and large (ii) reconciliations.

All models are estimated using the ordered probit regression, where *Rating* is an ordered dependent variable on a scale from 1 to 8. Other variable definitions are provided in Appendix 1. Estimated models are of the form:

Rating = *f* (*IntCov*1, *IntCov*2, *IntCov*3, *IntCov*4, *ROA*, *LTD Leverage*, *TD Leverage*, *Size*, *CI*, *Loss*)

All continuous variables are winsorized at the 1^{st} and 99^{th} percentiles. All models are estimated with White standard errors adjusted to account for correlation within firm clusters.