Mandatory IFRS Adoption and the Usefulness of Accounting Information in Predicting Future Earnings and Cash Flows

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This version: April 2019

[§] We gratefully acknowledge helpful comments received from Aida Sijamic Wahid, Oktay Urcan, Zach Wang and seminar participants at Rutgers University.

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Abstract

We examine whether the mandatory adoption of International Financial Reporting Standards (IFRS) has changed the usefulness of accounting information in predicting future earnings and cash flows *out-of-sample*. Using a sample of firms from European Union countries that mandatorily adopted IFRS in 2005, we find the out-of-sample earnings and cash flows forecasts derived from alternative accounting models become significantly more accurate after IFRS adoption. The accuracy, however, varies with the strength of legal and regulatory enforcement. Firms in strong enforcement countries experience larger improvements in earnings forecast accuracy than firms in weak enforcement countries but the opposite happens for cash flow forecasts. Accruals are useful in the prediction of both earnings and cash flows, but again their usefulness varies with the strength of the legal and regulatory environment. Portfolios of stocks based on the out-of-sample forecasts earn economically significant 12-month ahead hedge returns after IFRS adoption, which corroborates the detected forecast accuracy improvements. Overall, the study contributes to the IFRS literature by providing new evidence that an important dimension of accounting quality, predictive ability, has improved after mandatory IFRS adoption.

JEL Classification: M41; G15; G17; G18

Keywords: IFRS; out-of-sample prediction; earnings; cash flows

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1. Introduction

The adoption of the International Financial Reporting Standards (IFRS) by more than 100 countries in recent years has created a new line of research in accounting that examines the economic and accounting effects of these standards. Researchers have examined economic effects of switching from domestic accounting standards (DAS) to IFRS such as the impact on firms' cost of capital, valuation, liquidity, and financial analysts' decisions. They have also examined the effects of switching on various dimensions of accounting quality. The objective of all this research is to inform the debate of whether the switch from DAS to IFRS is worthwhile. Extant studies, reviewed below, have presented results indicating both desirable and undesirable effects from the switch and thus they further fuel the debate. We add to this line of research by investigating the following two questions: a) has the usefulness of accounting information in predicting future earnings and cash flows <u>out-of-sample</u> (OOS) changed after the mandatory adoption of IFRS? and b) if there is a change in this type of usefulness, is it conditional on institutional characteristics of the adopting countries that prior studies have found to play a significant role in the adoption of IFRS, such as legal enforcement, securities regulation, and the differences between their domestic accounting standards and IFRS?

We are motivated to investigate the out-of-sample predictability issue for the following reasons. First, in its conceptual framework the International Accounting Standards Board (IASB) explicitly indicates that "the objective of general purpose financial reporting is to provide financial information about the reporting entity that is useful to existing and potential investors, lenders, and other creditors in making decisions about providing resources to the entity.......

Consequently, existing and potential investors, lenders, and other creditors need information to help them assess the prospects for future net cash inflows to an entity" (IASB 2010). Therefore, testing whether IFRS has achieved this objective is critical in evaluating a potential benefit of the switch from DAS to IFRS. Based on insights from the forecasting literature, we argue that the strongest test of this objective is by performing an out-of-sample prediction test of future earnings and cash flows because such a prediction is needed for making investment decisions in practice. A long debate in the forecasting literature has concluded that forecasting methods be evaluated for accuracy using out-of-sample tests rather than goodness of fit to past data (in-sample tests). Thus, Stock and Watson (2003, p. 791) argue that the most notable desirable characteristic of out-of-sample measures of forecast accuracy is "their ability to detect changes in parameters towards the end of the sample" and they recommend, "evaluations of predictive content also should rely on statistics that are designed to simulate more closely actual real-time forecasting". Elliott and Timmermann (2008, p. 44) further state that "if interest lies in testing for the presence of real time predictability under the conditions facing actual forecasters in finite samples, then the use of a hold-out sample may make sense". We are not aware of any prior studies on IFRS performing such a test.[1]

Second, existing evidence on the effects of IFRS on predictability has been generated from the application of in-sample tests. Thus, using tests of coefficient differences from regressions of future cash flows on current earnings, Atwood et al. (2011) conclude that earnings reported under IFRS do not have a significantly stronger association with future cash flows than earnings reported under non-US DAS. Using tests of R-squared differences from the estimation of similar regressions, Barth et al. (2012) conclude that the power of current earnings to predict

[1] Fundamental analysis also requires out-of-sample earnings/cash flow forecasts for the estimation of intrinsic values. See Monahan (2017) for a comprehensive review.

one-year-ahead cash flows increased after IFRS adoption. Since the issue of whether IFRS is a more beneficial system than non-US DAS is important to firms and countries, we are motivated to examine it using the very demanding out-of-sample prediction tests that we view as required complementary tests. In other words, we examine whether the in-sample tests performed in prior studies "can withstand the robustness of an out-of-sample test, a test design that is closer to reality" (Poon and Granger 2003, p. 479).

Third, prior studies such as Byard et al. (2011), Tan et al. (2011), and Horton et al. (2013) show that financial analyst earnings forecast accuracy improves after IFRS adoption, while Daske et al. (2008) and Li (2010) find cost of capital declines after IFRS adoption. Various reasons, such as stronger enforcement, higher reporting quality, and more management earnings guidance, have been presented for these documented economic effects of IFRS adoption. It is also plausible that more accurate OOS earnings and cash flow prediction using the reported accounting numbers helps analysts improve their forecast accuracy and facilitates capital formation. This potential link thus further motivates our OOS tests.

Our analyses focus on comparisons of OOS prediction performance between the pre- and post-IFRS periods. The sample period spans 1999-2014 and we report results from a constant sample of firms that mandatorily adopted IFRS in 2005.[2] The advantage of a constant sample is that it controls for confounding effects because the same firm is compared before and after IFRS adoption. However, the constant sample does not control for economy-wide conditions that may differentially affect prediction performance in the periods before and after adoption. As in Ahmed et al. (2013), we control for economy-wide conditions unrelated to IFRS adoption by constructing a constant matched benchmark sample using non-IFRS firms that have used

[2] We start the sample in 1999 because data availability before 1999 is low.

domestic GAAP throughout the sample period 1999-2014. We thus analyze prediction performance using four subsamples: a) pre-2005 IFRS, b) post-2005 IFRS, c) pre-2005 non-IFRS, and d) post-2005 non-IFRS.

As in many prior related studies, we select our sample countries from the European Union (EU) countries that mandatorily adopted IFRS in 2005 and require a country to have a minimum number of observations per year to be included in our sample. This is to ensure that we have sufficient data to run cross-sectional country-year regressions for the construction of OOS forecasts and to balance the representativeness of sample countries. As a result, we have a primary IFRS sample consisting of 921 firms from 14 EU countries with the required data. To form OOS forecasts, we derive country- and year-specific parameter estimates from four accounting-based prediction models with varying levels of breakdown of accounting earnings into accruals and cash flows. The breakdown allows us to assess the incremental usefulness of accruals relative to cash flows in the OOS prediction process, an issue that has not been examined in the IFRS setting. We then evaluate the OOS predictions of future earnings and cash flows by statistically testing the difference in forecast accuracy between the pre-2005 and post-2005 subsamples, as well as the difference-in-differences between the IFRS and non-IFRS samples. We further analyze the change in forecast accuracy conditional on country-specific institutional characteristics. In our last test, we examine the economic significance of the OOS forecasts to see whether there is consistency with their statistical significance. For this, we form portfolios of stocks using our OOS forecasts and calculate the hedge returns each portfolio earns over the next 12 months. We then compare the hedge returns between the pre-2005 and post-2005 periods.

Overall, our results suggest significant improvements in the post-2005 period across all our models and tests. Thus, the improvements are present in the prediction model regression (in-sample) results, in the out-of-sample forecast accuracy results, and in the portfolio hedge returns results. The implication is that in our sample, on average, IFRS significantly increased the predictive ability of accounting numbers relative to DAS. However, the improvements are not uniform—they depend on the strength of the legal and regulatory enforcement in each country. In fact, an interesting result that calls for further research is that firms in strong enforcement countries experience larger improvements in earnings forecast accuracy than firms in weak enforcement countries but the opposite is the case for cash flow forecasts. Accruals are incrementally useful relative to cash flows in the prediction of both earnings and cash flows, but their usefulness also varies with the strength of the legal and regulatory environment.

This study is the first to focus on the usefulness of accounting information in an out-of-sample forecasting context in the literature relating to IFRS and international convergence. It contributes to that literature by examining an important dimension of accounting quality, the predictive ability of accounting numbers. The study conducts the examination in a comprehensive way following the recommendation of the forecasting literature. That is, both in-sample and out-of-sample prediction tests are performed along with economic significance tests. In this way, the robustness of results becomes more convincing. For example, our results confirm that the in-sample results of Barth et al. (2012) that the adoption of IFRS increased the predictability of cash flows relative to DAS is robust.

The method of OOS prediction evaluation can be used in future studies to examine other dimensions of IFRS accounting quality and economic consequences. For example, the prediction usefulness of IFRS-based accrual components deserve further examination. Another study may look at whether improvements in OOS prediction have caused desirable economic effects of IFRS adoption such as lower cost of capital and higher liquidity documented in prior studies. Yet another study can examine whether the substitution between accrual-based and real earnings management after IFRS adoption, as suggested by prior studies, has an impact on forecast accuracy.

The rest of the paper is organized as follows. Section 2 reviews the related literature and section 3 outlines the research design. In Section 4, we present the main empirical results. Section 5 discusses additional analyses. Section 6 concludes.

2. Related Literature

The IFRS literature is large and growing. We only review a few key studies relevant to our research objectives and refer the reader to De George et al. (2016) who offer a comprehensive review of IFRS-related research. The relevant literature on IFRS adoption can be classified into two branches, one examining the accounting quality implications of IFRS adoption while the other studying the economic effects thereof. In the first branch, various characteristics of accounting quality have been examined. Barth et al. (2008) find that in the post-adoption period firms voluntarily applying International Accounting Standards (IAS)[3] generally evidence less earnings management, more timely loss recognition, and more value relevance of accounting amounts than do firms not applying IAS. Atwood et al. (2011) examine the ability of reported earnings to predict future earnings and cash flows and find a) predictive ability does not differ between IFRS and non-US DAS earnings, and b) the predictive ability of earnings reported under US GAAP is stronger than that of earnings reported under IFRS. Barth

[3] We use IAS and IFRS interchangeably in this paper to refer to the prevailing international accounting standards.

et al. (2012) do not confirm the first result of Atwood et al. (2011) but they confirm the second in a study that examines another characteristic of accounting quality, comparability. In general, Barth et al. (2012) find that IFRS firms have significantly greater accounting system and value relevance comparability with US firms when they apply IFRS than when they applied non-US DAS. They also show that based on most metrics comparability is significantly greater for firms that adopt IFRS mandatorily, for IFRS firms in countries with common law legal origin and strong enforcement, and for firms adopting IFRS in recent years.

Ahmed et al. (2013) examine the effects of mandatory IFRS adoption on accounting quality and find an increase in income smoothing, an increase in aggressive reporting, and a significant reduction in the timeliness of loss recognition for IFRS firms relative to benchmark firms after mandatory IFRS adoption. The results suggest a decrease in accounting quality following IFRS adoption.

The other branch of the IFRS literature studies the economic effects of IFRS adoption. Armstrong et al. (2010) and Christensen et al. (2007) use market reactions to various events associated with anticipated adoption of IFRS to gauge the expected total economic effect. They find on average IFRS adoption was perceived to be beneficial and the perceived benefit varies with the quality of the firm's pre-adoption information environment and the distance between the domestic accounting standards and IFRS. Other studies use the first few years of data after the mandatory IFRS adoption to examine the ex post effects. Daske et al. (2008) examine the capital market effects around IFRS adoption in 26 countries and find an increase in market liquidity, a decrease in firms' costs of capital, and a corresponding increase in equity valuations (measured as Tobin's q) after mandatory IFRS adoption. They also show that there is significant cross-sectional difference in the liquidity and cost of capital effects—capital market benefits exist only in countries with strict enforcement regimes and in institutional environments that provide strong reporting incentives. Li (2010) finds similar results with regard to the cost of capital for EU firms.

Landsman et al. (2012) present evidence that the information content of earnings announcements increased in 16 countries that mandated IFRS adoption, relative to the 11 countries that retained DAS; the effects are stronger in countries with stronger legal systems. They attribute the increased information content to three sources: smaller reporting lag, higher analyst following, and higher foreign investment. Byard et al. (2011), Tan et al. (2011), and Horton et al. (2013) examine firms' information environment surrounding the mandatory introduction of IFRS and find that analyst forecast properties like forecast accuracy, analyst following, and forecast dispersion improve after the mandatory adoption of IFRS. However, the documented effects vary substantially by firm, industry, and country. DeFond et al. (2011) find that foreign mutual fund ownership increases following mandatory IFRS adoption, but only in countries with strong implementation credibility, and that the increase is greater in companies with larger increases in uniformity. Wahid and Yu (2014) show that the tendency to underinvest in investee firms that apply different accounting standards from investor firms weakens when either the investee or the investor adopt IFRS. They attribute this effect to investor's familiarity with IFRS standards. In interpreting findings in academic research that attribute various effects to IFRS adoption, Christensen (2012) and Christensen et al. (2013) caution that concurrent changes in enforcement and reporting incentives, rather than the change in accounting standards, may well be the real cause.

This study belongs to the branch that examines the accounting quality implications of IFRS adoption. We seek to add to the literature by shedding more light on accounting quality implications following IFRS adoption. We focus on the predictive value characteristic of accounting quality because it is not only important for the decision relevance of accounting numbers but it is also important for the research design of accounting studies as Monahan (2017) points out. With the application of out-of-sample prediction tests, we hope to accomplish two things. First, examine the robustness of prior results given that out-of-sample tests are argued to be more appropriate for forecast evaluation as they not only mirror real world forecasting activities but also overcome the limitations of in-sample tests (see, e.g., Elliott and Timmermann 2008 and Lev et al. 2010 for more discussions).[4] Second, encourage the use of out-of-sample tests in prediction studies given their critical role in validating alternative prediction models.

We also note that a clear link on how the effect of IFRS adoption on accounting quality translates into the documented economic effects is currently missing from the literature. Our study represents a necessary first step toward discovering the mechanisms through which detected accounting quality implications of IFRS adoption translate into documented economic effects. Currently, only Landsman et al. (2012) shows one such mechanism. That is, the reduced reporting lag under IFRS contributes to the increase in the information content of earnings announcements. More mechanisms can be at work and the improved out-of-sample earnings and cash flow prediction, a critically important quality of accounting information for investors, can be an IFRS accounting effect that helps analysts improve their forecast accuracy and facilitates capital formation. Future research could use the OOS prediction method to explain some of the positive economic effects documented by prior studies.

[4] Out-of-sample tests have not been very common in the accounting literature. Some representative studies include Finger (1994), Lorek and Willinger (1996), Fairfield and Yohn (2001), Kim and Kross (2005), Fairfield et al. (2009), Lev et al. (2010), Eng and Vichitsarawong (2017), and Vorst and Yohn (2018). Some recent studies have complemented in-sample prediction tests with out-of-sample tests, e.g. Li et al. (2014), and Nallareddy and Ogneva (2017), a trend that is likely to continue.

3. Research Design

This section introduces our research design in four parts: a) description of the prediction models we examine, b) description of the out-of-sample performance evaluation metrics we employ, c) description of our sampling procedure, and d) description of the bootstrapping approach we use to draw inferences from comparisons of prediction performance across the subsamples.

3.1 Prediction Models

The prediction models we employ are cross-sectional models following the recommendation of Fama and French (2000) that is consistently followed in accounting studies (e.g. Lev et al., 2010, Vorst and Yohn, 2018. The construction of the specific models and variable definitions follow Barth et al. (2001). That is, we break down earnings into accruals and cash flow components and use them to predict next period earnings and cash flows. More specifically, our four prediction models, Model 1 through Model 4, are:

$$EARN_{t+1} = \beta_0 + \beta_1 * CFO_t + \varepsilon_t \tag{1}$$

$$EARN_{t+1} = \beta_0 + \beta_1 * EARN_t + \varepsilon_t \tag{2}$$

$$EARN_{t+1} = \beta_0 + \beta_1 * CFO_t + \beta_2 * ACCR_t + \varepsilon_t \tag{3}$$

$$EARN_{t+1} = \beta_0 + \beta_1 * CFO_t + \beta_2 * \Delta AR_t + \beta_3 * \Delta INV_t + \beta_4 * \Delta AP_t + \beta_5 * DP_t + \beta_6 * OTHER_t + \varepsilon_t \tag{4}$$

Where,

EARN:	Earnings before extraordinary items
CFO:	Net cash flow from operating activities, adjusted for the accrual portion of extraordinary items and discontinued operations.

ACCR: Accruals, defined as *EARN – CFO*

ΔAR: Decrease (increase) in accounts receivable

ΔINV: Decrease (increase) in inventory

ΔAP: Increase (decrease) in accounts payable

DP: Depreciation and amortization expenses

OTHER: Other accruals, defined as *EARN – (CFO + ΔAR + ΔINV – ΔAP – DP).*

All variables are scaled by beginning total assets. Each of these models is estimated every year for each country. This process generates country- and year-specific regression coefficients that we use to derive out-of-sample forecasts. We use the same models for the prediction of next year's cash flow from operations as well. The reasons for using more than one model are to examine whether a) out-of-sample prediction inferences are consistent across different models and not sensitive to a specific model, and b) accruals have incremental to cash flow usefulness in predicting future earnings and cash flows.[5]

3.2 Out-of-sample Prediction Performance Evaluation

We get out-of-sample firm- and year-specific forecasts by using the country- and year-specific estimated coefficients from each of the above four prediction models and the current period accounting numbers. We then calculate firm- and year-specific prediction errors as the difference between the actual and predicted values of earnings or cash flow from operations. By estimating country-specific regressions, we take into consideration possible effects that reporting incentives and other country-specific factors may have on the quality of accounting information,

[5] We also estimated each model every year for seven industries by pooling yearly data across all countries. The seven industries are: a) Consumer non-durables, b) consumer durables, c) manufacturing, d) business equipment, e) wholesale, retail, and some services, f) health care, medical equipment, and drugs, and g) all other industries. The inferences we derive from this industry and year analysis are largely the same as those from the country and year analysis reported below.

including its predictive ability.[6] The following example of the prediction of earnings illustrates our prediction procedure.

To predict out-of-sample earnings for year 2003 using Model 3 and evaluate the prediction, we use actual accounting numbers for 2001 and 2002 as follows:

1. Estimate cross-sectionally for each country the following regression:

$EARN_{2002} = \beta_0 + \beta_1 * CFO_{2001} + \beta_2 * ACCR_{2001} + \varepsilon_t$

2. Predict out-of-sample earnings for 2003 for each firm in a given country by using the country-specific estimated coefficients and actual CFO and ACCR values for 2002: $\widehat{EARN}_{2003} = \widehat{\beta_0} + \widehat{\beta_1} CFO_{2002} + \widehat{\beta_2} ACCR_{2002}$

3. Determine the prediction error for 2003 for each firm in a given country: $FE_{2003} = EARN_{2003} - \widehat{EARN}_{2003}$.

The same procedure is repeated for every sample year. We evaluate the out-of-sample prediction performance as listed below:

MAPE:	Mean absolute prediction error, with prediction error calculated as (actual–forecast)
MPE:	Mean prediction error
RMSE:	Root mean square prediction error

MAPE informs about the accuracy of the prediction where a larger value of *MAPE* implies less accurate forecasts. *MPE* can be interpreted as a measure of prediction bias; a positive *MPE* indicates a lower value of forecasts relative to actual values (pessimistic forecasts).

[6] Ahmed et al. (2013) and Barth et al. (2012) try to tease out these other factors before carrying out their main tests. As long as the relations between these factors and one-year-ahead earnings and cash flows remain similar between the two sub periods, confounding effects should be minimal.

RMSE is another summary measure of accuracy and measures the predictability of actual values using forecasts where a larger value of *RMSE* implies less predictable actual values.

In addition to the above three performance measures, we also examine the ability of our out-of-sample forecasts to predict future stock returns in additional analyses. This is another very demanding and more direct performance measure than the other three because it directly evaluates the usefulness of the forecasts in stock investing.

3.3 Samples

We follow prior studies (Barth et al. 2012; Ahmed et al. 2013) and employ a constant sample to control for confounding effects in studying the impact of the mandatory adoption of IFRS on the usefulness of accounting information. To construct our primary sample using Compustat Global,[7] amongst European countries that mandatorily adopted IFRS in 2005, we select a group of firms that have data available to compute the main variables of the prediction models in each year between 1999 and 2014. We start the sample in 1999 because requiring data before 1999 in a constant sample would greatly reduce the number of sample firms. If we refer to the sample period using base years (year *t*), the sample period spans 2000-2013.[8] We eliminate from the sample base years 2004 and 2005 so that we do not mix numbers from DAS and IFRS when we estimate the prediction models for 2005 and avoid potential confounding effects from the transition. We end up with 12 years in the sample period, four years (2000-2003) in the pre-IFRS adoption period and eight years (2006-2013) in the post-IFRS adoption period.[9]

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[7] According to Dai (2012), "Compustat Global features greater coverage of large companies in more developed countries and provides a wider range of accounting data items than any other databases". Compustat Global suits our purpose well because we employ a constant sample that tends to include larger firms from more developed EU countries.

[8] We need 1999 as we use beginning total assets to scale the variables. We choose our sample period after considering the need for a time series with adequate length from recent years, and the fact that the constant sample design has a high filter rate for surviving firms. This sample period is similar to many recent studies on IFRS.

[9] These are the lengths of the sample periods for in-sample analysis. When we move to out-of-sample performance evaluation, we lose one year from the pre-2005 period and another year from the post-2005 period. Specifically, we

To isolate the effects of the mandatory adoption of IFRS, we construct a benchmark sample using US GAAP firms from Compustat North America and firms that did not adopt IFRS during the entire sample period (non-IFRS firms) from Compustat Global.[10] Similar to Barth et al. (2008), Barth et al. (2012), and Ahmed et al. (2013), we match the primary sample firms and benchmark firms on four dimensions, namely, industry, size as measured by market value of equity, book-to-market ratio, and profitability as measured by return on assets.[11] In addition, we match the primary sample firms and benchmark firms on the strength of national legal enforcement as reported in Kaufmann et al. (2007) to control for its effect on corporate financial reporting and to better assess the change in prediction performance. Christensen (2012) and Christensen et al. (2013) argue that changes in enforcement and reporting incentives may be more important than changes in accounting standards in explaining many of the purported IFRS effects. Specifically, following prior studies such as Ahmed et al. (2013), we match each IFRS sample firm operating in a high (low) legal enforcement country with a benchmark firm that belongs to the same industry group, operates in a high (low) legal enforcement country, and yields the smallest distance measure computed as follows:

$$((MV_f - MV_g)/MV_f)^2 + ((BTM_f - BTM_g)/\ BTM_f)^2 + ((ROA_f - ROA_g)/\ ROA_f)^2$$

where the subscript *f* indicates IFRS sample and *g* is benchmark sample. Market value of equity (MV), book-to-market ratio (BTM), and return on assets (ROA) are measured as the average of

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estimate prediction models each year between 2000 and 2002 for the pre-IFRS adoption period and between 2006 and 2013 for the post-IFRS adoption period. Correspondingly, the out-of-sample forecast period covers three years between 2001 and 2003 for the pre-IFRS adoption period and eight years between 2007 and 2014 for the post-IFRS adoption period.

[10] Our set of non-IFRS countries is based on Ahmed et al. (2013) including Argentina, Brazil, Chile, India, Israel, Korea Rep., Malaysia, Mexico, Pakistan, Taiwan, Thailand, Japan, New Zealand, and the US. We exclude Canada because Canada mandatorily adopted IFRS in 2011.

[11] We follow Barth et al. (1998) and define 15 industries: mining and construction, food, textiles, printing, and publishing, chemicals, pharmaceuticals, extractive industries, durable manufacturers, computers, transportation, utilities, retail, financial institutions, insurance and real estate, services, and others.

the pre-IFRS adoption sample period 2000-2003. Matching is done without replacement so that we can have a unique match for each firm. Together we have four subsamples, namely pre-2005 (pre-IFRS adoption) IFRS subsample, post-2005 (post-IFRS adoption) IFRS subsample, pre-2005 benchmark subsample, and post-2005 benchmark subsample.

3.4 Comparing and Testing the Changes in Prediction Performance

We employ a bootstrapping approach similar to that in prior studies (e.g. Barth et al. 2012), to test the significance of the change in prediction performance between periods in the IFRS and benchmark samples as well as the difference-in-differences between the IFRS and benchmark samples. Particularly, we randomly select, with replacement, observations from each of the four subsamples to create representative samples each year. We then compute *MAPE, MPE*, and *RMSE* for each representative sample every year. We take the average of the corresponding yearly *MAPE, MPE,* and *RMSE* in the pre- and post-2005 periods. We can then calculate the differences in *MAPE, MPE,* and *RMSE* between periods in the IFRS sample and the benchmark sample as well as the difference-in-differences between the IFRS and benchmark samples. The difference-in-differences between the IFRS and benchmark samples inform us whether the change in prediction performance is attributable to the mandatory adoption of IFRS rather than the reflection of a time trend or other confounding factors. The procedure is repeated 1,000 times to obtain empirical distributions of the differences in *MAPE, MPE,* and *RMSE* between periods for the IFRS and benchmark samples and the difference-in-differences between IFRS and benchmark samples. The empirical distributions of the differences between periods and the difference-in-differences between the IFRS and benchmark samples are not symmetric about zero. Following Ahmed et al. (2013), we determine the differences between periods and the difference-in-differences between the IFRS and benchmark samples as statistically significant at the 1% (5% and 10%) level if the confidence intervals bounded by the top and bottom 0.5th (2.5th and 5th) percentiles of the empirical distributions do not contain zero. We also use a similar procedure for the comparison of in-sample coefficient estimates.

4. Empirical Results

In this section, we present the main findings from our empirical analysis. We begin by describing the data and main variables and then discuss the in-sample regression analysis. We next present results of the out-of-sample performance evaluation and complete the analysis with tests on the cross-sectional variations of the main effects conditional on institutional characteristics.

4.1 Data and Variables

As discussed in Section 3.3, we draw our primary sample from EU countries that mandated adoption of IFRS in 2005. We begin constructing the sample by selecting companies that mandatorily switched from DAS to IFRS in 2005. Same as in Barth et al. (2013), companies that are cross-listed in the US and financial companies (with SIC between 6000 and 6999) are excluded. We then define the main variables used in the prediction models 1 through 4. To ensure consistency in measuring the variables, all raw data are translated into US dollar amounts using the appropriate exchange rates.[12] When cash flow variables, such as *CFO*, *ΔAR*, *ΔINV*, and *ΔAP* are missing in Compustat Global, we use the consecutive changes in the corresponding balance sheet items instead, following Barth et al. (2001).[13] For example, when the net operating cash flow variable from the statement of cash flows is missing, we define accruals as change in

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[12] For balance sheet items, spot exchange rates at the balance sheet dates are used. For income statement and statement of cash flow items the average exchange rates over the fiscal year are used. The exchange rate data are obtained from the Federal Reserve Bank Foreign Exchange Rates (H10 report) database.

[13] There are many missing values for statement of cash flow variables in Compustat Global Fundamental Annual files. Using balance sheet data allows us to have a sample that is about 20% larger than otherwise. As a robustness check, we limit our variables to available statement of cash flow data items and the main results remain the same.

non-cash working capital minus depreciation and amortization, same as in Sloan (1996), and cash flow from operations as earnings minus accruals. We further require firms to have positive sales revenue and total assets and data to calculate all the variables used in Models 1 through 4. We also require a country to have a minimum number of observations per year in the sample period to ensure we have sufficient data to run country-year regressions to generate OOS forecasts. These procedures give us a final constant primary sample of 921 companies from 14 EU countries, or 11,052 firm-year observations between 2000 and 2003 (pre-IFRS adoption prediction period) and between 2006 and 2013 (post-IFRS adoption prediction period).[14] All financial statement variables are deflated using beginning total assets. All variables are winsorized at the top and bottom one percentile of the respective distributions to mitigate undue influence of outliers.

We construct a benchmark sample using non-IFRS firms (including US firms) throughout the entire sample period. We match each IFRS sample firm with a non-IFRS firm that has non-missing data on all of the main variables during the same sample period (1999-2014) using a five-dimensional matching (industry, level of legal enforcement, market value, book-to-market, and profitability), as described in Section 3.3. Through the above sampling procedures, we now have two primary samples, namely the IFRS sample and the benchmark sample.

Table 1 presents descriptive statistics for both samples. Panel A presents the number of observations across countries in the IFRS and benchmark samples. Among the 14 EU countries in the IFRS sample, Great Britain has the largest representation at 33.2%, followed by France, Sweden, and Germany. These four countries together constitute over 70% of the entire IFRS sample. Also reported in Panel A are the partitions of the sample into high versus low legal

[14] Countries with insufficient number of observations each year over the sample period, including Spain, Greece, and Portugal, are pooled to generate the yearly cross-sectional coefficients of the prediction models.

enforcement countries. Using the rule of law score for 2005 from Kaufmann et al. (2007), we denote countries with scores lower than the median rule of law score (1.3) as low enforcement countries. Among the 14 EU countries, only four are designated as low enforcement countries—Italy, Spain, Greece, and Portugal. There are 55 firms from these four countries and their observations constitute 6% of the IFRS sample. We also use the securities regulation strength score from Leuz (2010) to classify countries into high versus low securities regulation subsamples. That is, countries such as Belgium, Switzerland, Germany, Spain, Finland, Greece, Norway, and Sweden that have lower than the median securities regulation strength index (1.5) are classified as the low securities regulation subsample, with a total of 315 firms, or about 34% of our IFRS sample. Another measure we use in our subsample analysis is the measure of differences of the country's original DAS from IFRS, taken from Bae et al. (2008), which captures differences between accounting standards along 21 key accounting areas. Countries with fewer than nine differences in key accounting areas comprise the low difference subsample.[15] The primary benchmark sample consists of firms from India, Israel, Japan, and the US. Observations from Japan and the US comprise 94% of the benchmark sample.

Panel B of Table 1 shows the distributional characteristics of the IFRS sample in both pre-2005 and post-2005 sample periods. The size distribution of the sample is skewed to the right, with mean (median) total assets being \$908.1 million (\$171.1 million) before 2005 and \$1,991.4 million (\$343.1 million) after 2005. Average earnings or equivalently return on assets is only 1.2% before 2005 and rises to 4.1% after 2005. Average total accruals scaled by total assets are equal to -0.066 before 2005 and -0.043 after 2005, while the average total cash flow from operations scaled by total assets increases from 0.079 to 0.084. The general pattern of the

[15] The cutoff is chosen to ensure sufficient benchmark sample can be partitioned into the high difference subsample.

composition of earnings is similar to that observed for US GAAP samples in earlier studies such as Sloan (1996) and Richardson et al. (2005).

Also in Table 1, Panel B, we can see that the size distribution of the benchmark sample is similar to the IFRS sample, both skewed to the right. The mean (median) total assets amount to \$690.5 million (\$151.1 million) before 2005 and \$1,233.7 million (\$250 million) after 2005. For a quick comparison, the mean (median) total assets of the Compustat population are equal to \$2,257.9 million (\$117 million) before 2005 and \$3,727.4 million (\$183.3 million) after 2005 over the sample period. The distributions of other main variables such as *EARN*, *CFO*, and *ACCR* are similar to those reported in prior literature such as Richardson et al. (2005). We also test whether mean and median differences of the variables are statistically significant between the two samples and find that to be the case; the observation is similar to what is reported in Ahmed et al. (2013). In general, the benchmark firms have smaller total assets (mean *AT* = \$690.5 million vs. \$908.1 million) and while the pre-2005 profitability ratio is the same, 1.2%, the IFRS firms show higher profitability after the IFRS adoption (*EARN* = 0.041 vs. 0.024). Although the matching practice does not significantly eliminate differences in market value (*LOGMV*) between the IFRS and benchmark samples, it appears that profitability and book-to-market ratios are comparable between the IFRS and benchmark firms in the matching period. In addition, the earnings components (*CFO*, *ACCR*, ΔAR, ΔINV, ΔAP, and *DP*) of the benchmark sample show consistency during the sample period, suggesting that accounting practices of the benchmark sample are relatively stable over time. Thus, the benchmark sample is appropriate for controlling for general economic trends unrelated to IFRS adoption.

4.2 In-sample Analysis

Table 2 presents results from the estimation of our prediction models. In Panel A we report the averages of the country-year cross-sectional regression coefficients and R^2 using Models 1 through 4 for predicting earnings and cash flow from operations for the IFRS sample. We also report the changes in the *CFO* and *EARN* coefficients from the pre-2005 period to the post-2005 period, along with the statistical significance of the changes derived from bootstrapping, similar to Barth et al. (2012). There are several notable observations.

First, in the top portion of Panel A reporting earnings regression results, Models 1 and 2 show that cash flow and earnings persistence is higher in the post-2005 (IFRS) period than in the pre-2005 (non-U.S. DAS) period. As the column before the last ($\Delta CFO/\Delta EARN$) shows, for these two models the mean difference pre-post in the *CFO* coefficients is -0.133 (0.438-0.571) and in the *EARN* coefficients is -0.026 (0.623-0.649), both differences highly significant. In addition, Model 3 coefficients show that in both the pre- and post-2005 periods, cash flows are more persistent than accruals, consistent with results from studies using U.S. data such as Sloan (1996). Furthermore, the persistence of both cash flows and accruals strengthens during the IFRS period, i.e. after 2005 (0.669 and 0.518 pre-2005 vs. 0.751 and 0.527 post-2005). These results show an improvement after IFRS adoption in predicting earnings relative to non-U.S. DAS applied in the pre-2005 period. Specifically, accruals become more informative during the IFRS period as shown in Model 4 because not only *DP* but also ΔAP and *OTHER* are significantly associated with future earnings in that period.

The results for the prediction of CFO_{t+1} (lower portion of Panel A) are similar to those for $EARN_{t+1}$ where again cash flows are more persistent than accruals (Model 3) and accruals become more informative after IFRS adoption (Models 3 and 4). Furthermore, Models 1 and 2 show that again cash flow and earnings persistence is higher in the post-2005 (IFRS) period than in the pre-2005 (non-U.S. DAS) period. That is, Δ*CFO/*Δ*EARN* shows that the mean difference pre-post in the *CFO* coefficients is -0.066 (0.474-0.540) and in the *EARN* coefficients is -0.036 (0.479-0.515), and both differences are highly significant. For these regressions, we observe higher mean R^2s in the post-2005 that in the pre-2005 period as in Barth et al. (2012).

Second, the last column in Panel A reports results from the difference-in-differences tests (DDs) for the *CFO* and *EARN* coefficients. The DDs for the earnings prediction models are all negative and significant implying that the improvements in persistence for the IFRS sample are significantly greater than the improvements for the benchmark sample. For example, a DD of -0.117 and a difference of -0.133 for the CFO coefficients of Model 1 imply a pre-post CFO coefficient difference (Δ*CFO*) of -0.016 for the benchmark sample. However, the DDs for the cash flow prediction models are all positive and significant implying that the improvements in persistence for the IFRS sample are significantly lower than the improvements for the benchmark sample.

The overall conclusion from the in-sample results is that the mandated IFRS adoption generated significant improvements in the prediction of both earnings and cash flows. This is more consistent with the conclusion in Barth et al. (2012) than that of Atwood et al. (2011). The issue we investigate next is whether these results from in-sample tests also hold when we perform out-of-sample tests. As we mentioned earlier, the forecasting literature points to the over-time instability of the in-sample parameter estimates as a cause for disagreement between in-sample and out-of-sample prediction results. Panel B of Table 2 reports the average coefficient estimates of the country-specific cross-sectional regressions in each year of the pre- and post-2005 sample periods for Model 4 and for both the IFRS and benchmark samples. A casual perusal of these results reveals noticeable intertemporal variability in the coefficient estimates. For example, the *CFO* coefficients vary from 0.523 to 0.88 in the IFRS sample and from 0.536 to 0.902 in the benchmark sample. The variation in accrual components coefficients is even larger. For instance, the coefficient on ΔAR ranges between 0.054 in 2008 and 0.487 in 2002 in the IFRS sample.[16] Whether this intertemporal variability in the coefficient estimates causes the out-of-sample prediction results significantly deviate from the in-sample results is an empirical question we investigate next.

4.3 Out-of-Sample Prediction Evaluation

Table 3 presents the main results from the out-of-sample prediction evaluation tests that relate to our first research question (whether prediction performance changed on average). The table reports results for the IFRS sample and differences between the IFRS and benchmark samples (difference-in-differences). First, Model 3, which breaks down earnings into cash flows and accruals, outperforms the other three models on *MAPE* and *RMSE*. Thus, in the post-2005 period Model 3 out-of-sample forecasts of $EARN_{t+1}$ and CFO_{t+1} have the lowest *MAPE* (0.046 and 0.051, respectively) and lowest *RMSE* (0.076 and 0.075, respectively) relative to the other three models. In terms of forecast bias (*MPE*), out-of-sample forecasts of $EARN_{t+1}$ tend to be lower than actual values (pessimistic) in the pre-2005 period but higher than actual values (optimistic) in the post-2005 period (column (3)). Despite the directional change in bias, the magnitude of bias is generally smaller in the post-2005 period. The pattern on out-of-sample forecasts of CFO_{t+1} in the pre- or post-2005 period is not as clear as forecasts of earnings but it also appears that the magnitude of bias is generally smaller in the post-2005 period (column (4)).

[16] The goodness of fit of Model 4 is also noteworthy where R^2 is relatively low during the financial crisis years (2007-2008). This observation further cautions for inferences of the effect of IFRS adoption relative to DAS based on the goodness of fit of in-sample prediction models.

Second, *MAPE* and *RMSE* exhibit statistically significant changes in both difference (pre-post) and difference-in-differences (pre-post of IFRS firms less pre-post of benchmark firms) tests based on the bootstrapping approach. The forecast accuracy evaluation metric *MAPE* has significantly positive values in the Pre-Post test indicating higher accuracy in the post-2005 period than in the pre-2005 period for both predictions of earnings and cash flows. The result still holds after controlling for the corresponding change in the benchmark sample; the positive difference-in-differences *MAPE* indicates significantly greater improvements in forecast accuracy after IFRS adoption than the improvements experienced by the benchmark sample.

Third, Model 1 shows the greatest improvement in the out-of-sample forecast accuracy of earnings with Pre-Post *MAPE* value of 0.011, DD MAPE value of 0.012, *RMSE* value of 0.018, and DD RMSE value of 0.016. The implication is that cash flows became more informative about future earnings in the post-2005 (IFRS) period and made the gap smaller relative to the benchmark sample. Model 2 also shows the greatest improvement in the out-of-sample forecast accuracy of cash flows with Pre-Post *MAPE* value of 0.012, DD MAPE value of 0.012, *RMSE* value of 0.022, and DD RMSE value of 0.015. Thus, the implication is that earnings became more informative about future cash flows in the post-2005 (IFRS) period and made the gap smaller relative to the benchmark sample. Models 3 and 4 also show prediction improvements but smaller than those of Models 1 and 2. These results show that after IFRS adoption, the out-of-sample forecasts derived using the four models are more accurate and can better predict future earnings and cash flows than before IFRS adoption.

Fourth, comparisons of forecast accuracy between models evaluate the usefulness of accruals in the prediction process. The results indicate that the accuracy of Model 3 earnings and cash flow forecasts is significantly higher than that of Models 1, 2, and 4 (at the 5% level or better). The implication is that total accruals are incrementally informative to cash flows but the breakdown into accrual components reduces accuracy and that appears to be the case in both the pre- and post-2005 periods. These results contrast the in-sample results of Table 2 in which Model 4 has the highest R^2 among the four models and confirms the arguments in the forecasting literature that high in-sample goodness of fit may not yield high forecast accuracy.

In sum, the answer to our first research question is that the mandatory IFRS adoption increased the usefulness of accounting information in predicting out-of-sample future earnings and cash flows. The out-of-sample results are consistent with our in-sample results indicating that the variability in our in-sample coefficients was not large enough to cause a disagreement between the in- and out-of-sample results. In addition, they are consistent with the in-sample results of Barth et al. (2012) who find earnings to be more informative about future cash flows after IFRS adoption. The overall increased usefulness can be due to various factors. Based on our models, after IFRS adoption total accruals appear to have become more informative. Another factor can be the increased income smoothing after mandatory IFRS adoption that Ahmed et al. (2013) report which can lead to more predictable earnings and cash flows.

4.4 Cross-sectional Variation in the Main Effects

Our second research question relates to the cross-sectional variation in the prediction effects caused by mandated IFRS adoption. We address this question by partitioning the primary sample and repeating the out-of-sample prediction evaluation for the high and low enforcement subsamples, for the high and low securities regulation subsamples, and for the high and low differences from IFRS subsamples separately; partitioning is based on institutional characteristics as described in Section 4.1. We also repeat the bootstrapping procedure on the new subsamples to obtain empirical distributions of *MAPE*, *MPE* and *RMSE*, and carry out statistical tests. To save space, in all the subsample analyses, we only report the out-of-sample prediction accuracy *MAPE* results for $EARN_{t+1}$ and CFO_{t+1} in the IFRS sample, while suppressing the results for *MPE* and *RMSE* and for the benchmark sample.[17]

Table 4 presents the prediction accuracy results on the high and low legal enforcement IFRS subsamples. These results are best viewed together with the full sample *MAPE* results presented in Table 3. With respect to the out-of-sample forecasts of earnings, the high legal enforcement subsample results in Table 4 closely resemble those in Table 3 which shows that it is the high legal enforcement countries driving the main results of statistically significant improvements in forecast accuracy after the mandatory IFRS adoption. Thus, column (1) shows that *MAPE* for Pre-Post is positive and significant for all four models implying increases in accuracy after IFRS adoption. In addition, *MAPE* for difference-in-differences is also significantly positive for all models indicating significantly greater improvements in forecast accuracy after IFRS adoption than the improvements experienced by the benchmark sample. The low legal enforcement countries appear to experience declines in out-of-sample earnings forecast accuracy after IFRS adoption. Thus, column (2) shows that *MAPE* for Pre-Post for all models and difference-in-differences for Models 2 and 4 are significantly negative. These results suggest decreases in accounting quality in the low legal enforcement countries after IFRS adoption.

Columns (3) and (4) of Table 4 show that both high and low legal enforcement countries experience improvements in the forecast accuracy of cash flows after IFRS adoption and the improvements appear to be greater in low legal enforcement countries. Thus, the *MAPE* for Pre-Post and for DDs in column (4) are larger than those in column (3). This is interesting considering the in-sample findings in Barth et al. (2012) that high legal enforcement countries

[17] Results for the benchmark sample are available from the authors upon request.

witness greater cash flow comparability with US GAAP after IFRS adoption where voluntary IFRS adoption is also considered.

In terms of the usefulness of accruals, columns (1) and (2) of Table 4 show that Model 3 has significantly higher accuracy in the prediction of earnings in both high and low legal enforcement, i.e. total accruals are incrementally informative to cash flows. However, columns (3) and (4) show that is not the case in the prediction of cash flows. In high legal enforcement, accruals are not incrementally informative to cash flows in either period (Models 3 and 4 are not better than Model 1). In low legal enforcement, total accruals are informative in the pre-2005 period while Model 4 shows the highest accuracy in the post-2005 period (accrual components are informative). Taken together, we find that the level of legal enforcement plays a role in the out-of-sample prediction of earnings and cash flows.

Table 5 reports results from the tests that examine the effect of securities regulation. For forecasts of both earnings and cash flow (columns 1-4), the *MAPE* for Pre-Post and for DDs are positive and significant across all four models. The implication is that both high and low securities regulation subsamples experience statistically better forecast accuracy after IFRS adoption and better relative to the benchmark sample. However, the magnitude of improvements in accuracy appears to vary with the strength of securities regulation where improvements are higher for earnings forecasts but lower for cash flow forecasts in countries with high securities regulation. Although the magnitude of improvements in forecast accuracy varies with the strength of securities regulation, the level of forecast accuracy is still higher in high securities regulation subsample after IFRS adoption. The results for the usefulness of accruals in earnings forecast accuracy are similar to those observed in Table 4, columns (1) and (2). As to cash flow forecast accuracy, in high securities regulation, total accruals are incrementally informative to cash flows in the pre-2005 period but such effect fades in the post-2005 period. In low securities regulation, accruals are not informative in the pre-2005 period (Model 1 shows the highest accuracy) but they become informative in the post-2005 period (Model 3 shows the highest accuracy). Overall, the level of securities regulation plays a role in out-of-sample predictions.

Table 6 presents the results of testing for the effect of the differences between the original DAS and IFRS. Similar to Table 5, for forecasts of both earnings and cash flow (columns 1-4), the *MAPE* for Pre-Post and for DDs are positive and significant across all four models. Thus, we observe significant improvements in forecast accuracy for both subsamples after IFRS adoption. In general, the magnitude of improvements varies with the level of differences between the original DAS and IFRS. That is, countries with low differences from IFRS experience greater improvements in earnings forecast accuracy than countries with high differences from IFRS whereas countries with low differences from IFRS experience smaller improvements in cash flow forecast accuracy than countries with high differences from IFRS. Columns (1) and (2) show that accruals are informative for the prediction of earnings in both the pre and post-2005 periods (Model 3 performs best). However, column (3) shows that in the case of high differences between IFRS and non-US DAS accruals do not help in the prediction of cash flows in either period (Model 3 is not better than Model 1). On the other hand, column (4) shows that in the case of low differences accrual components are informative only in the Post-2005 period. Overall, the level of differences between IFRS and non-US DAS plays a role in OOS predictions.

In sum, these subsample analyses reveal there are cross-sectional variations in the effects IFRS adoption has on the usefulness of accounting information in predicting future earnings and cash flows. The findings show that IFRS adoption coupled with variations in institutional characteristics has differential effects on the OOS forecast accuracy of earnings and cash flows and the usefulness of accruals. In particular, *earnings forecast accuracy* improves more in countries with high legal enforcement, high securities regulation, and low differences from IFRS whereas *cash flow forecast accuracy* improves more in countries with low legal enforcement, low securities regulation, and high differences from IFRS. This difference in prediction accuracy potentially relates to findings in recent research (e.g. Doukakis 2014; Ipino and Parbonetti 2016) that IFRS adoption has affected firms' earnings management strategies and deserves further investigation in future studies.

5. Additional Analyses

This section presents the additional analyses we conduct to ensure our main results are robust to certain assumptions and research design choices we make as well as the economic significance of improvements in out-of-sample forecast accuracy after IFRS adoption.

5.1 Using Only US GAAP Firms as Benchmark

Currently the control sample includes the US, Japan, India, and Israel, which do not use IFRS during our sample period. While this allows better matching, as it offers more variation in the institutional environment, a potential drawback is that the difference-in-differences results may have arisen from changes in the control group, rather than the treatment group. Alternatively, we use only US GAAP firms to form the benchmark sample to better control for environmental factors while relaxing the requirement of matching on the level of legal enforcement, as there is no such variation in the control sample—the US GAAP firms. The results (untabulated but available on request) are of similar tenor to those in Table 3, i.e. forecast accuracy improved after IFRS adoption. In addition, total accruals are incrementally to cash flows informative in predictions of earnings and cash flows. Furthermore, both the IFRS and matched US GAAP (inferred from the DDs) samples show a directional change in bias in earnings forecasts after 2005 with the magnitude of that change greater for the matched US GAAP sample, similar to bias (*MPE*) results reported in Table 3. This indicates that the benchmark sample is not driving the main effects discussed above in Section 4.3.[18,19]

5.2 Economic Significance of Out-of-Sample Predictions: Hedge Returns

Our out-of-sample results show statistically significant improvements in forecast accuracy after the adoption of IFRS. However, the statistical significance may not translate into economic significance that is important to the users of the predictions. To examine the economic significance in the change of the out-of-sample predictions before and after IFRS adoption, we examine hedge portfolio returns based on such out-of-sample predictions. For the IFRS sample, we form ten portfolios based on the ranking of the out-of-sample predictions derived from each of the four accounting models for each sample year (from 2002-2004 and 2008-2014). We calculate for each portfolio 12-month abnormal returns (size and book-to-market adjusted) starting from July of each sample year to June of the following year. We then in each year calculate hedge returns as the difference in portfolio returns based on the highest and lowest deciles.

Table 7 presents the results over the pre- and post-2005 periods for the whole sample and for each of the subsamples we analyzed above. Panel A shows that for the whole sample average hedge returns based on earnings predictions derived from all accounting models are negative before 2005 (ranging from -0.1% to -9.9%) whereas hedge returns are all positive post 2005

[18] We should be cautious, though, in generalizing these results as a comparison between IFRS and US GAAP, because the US GAAP sample is chosen to match firms in the IFRS sample and may not be representative of the general population of firms using US GAAP.

[19] Our inferences on the usefulness of accruals when we match only to US firms do not change from those discussed above.

(ranging from 2% to 7.7%). The increases in average hedge returns after IFRS adoption (Post-Pre line) are economically significant, ranging from 7.1% to 16.6% (hedge returns for Models 3 and 4 are statistically significant at the 10% and 5% level, respectively). The implication of these results is that the post-2005 earnings forecasts would be much more useful than the pre-2005 earnings forecasts to an investor with investments in all sample firms.

The remaining panels of Table 7 shed more light on how national institutions condition the economic significance in the change of earnings predictions after IFRS adoption. Thus, we present conditional analyses based on institutional characteristics in Panels B (legal enforcement), C (securities regulation), and D (differences from IFRS). In most cases, significant and positive changes in hedge returns after IFRS adoption occur in countries with high legal enforcement and high securities regulation, corresponding to our findings in the prediction accuracy analyses (Tables 4 and 5). In countries with high legal enforcement, changes in hedge returns range from 5.3% to 15.5% (for Models 3 and 4 the returns are statistically significant at 5% and 1% level, respectively). In countries with high securities regulation, changes in hedge returns range from 1.4% to 19.4% (for Model 2 and 3 the returns are statistically significant at 5% and 10% level, respectively). Overall, the results of Table 7 suggest that improvements in out-of-sample prediction accuracy after IFRS adoption are associated with improvements in economically significant hedge returns in the whole sample and in subsamples based on institutional characteristics. We should point out that our predictions come from very basic models and that the use of more elaborate models are likely to generate predictions that will yield stronger hedge returns results.

6. Conclusion

Whether IFRS adoption improves the quality of accounting information versus domestic accounting standards is a critical question for firms, investors, standard-setters, and regulators. We investigate an important dimension of IFRS quality, the usefulness of accounting information in predicting future earnings and cash flows out-of-sample, a prediction evaluation method recommended in the forecasting literature and applied in investment practice. To address the issue, we analyze a constant sample of firms from 14 European Union countries that mandatorily adopted IFRS in 2005.

We find significant improvements in accuracy of the out-of-sample forecasts derived from accounting models after IFRS adoption. Consistent with prior studies that examine other dimensions of accounting quality, we find the earnings and cash flow forecast improvements vary with the strength of legal enforcement and securities regulation, and with the differences between DAS and IFRS. However, our results show consistent differences between the accuracy of earnings and cash flow forecasts. Specifically, firms in strong enforcement (legal and regulatory) countries experience larger improvements in earnings forecast accuracy than firms in weak enforcement countries but the opposite appears to be the case for cash flow forecasts. On average, accruals are useful in the prediction of both earnings and cash flows in both the DAS and IFRS periods but again that usefulness varies with the strength of the legal and regulatory environment. We also assess the extent to which our out-of-sample forecasts can be useful in investing decisions. We find portfolios of stocks based on the out-of-sample forecasts earn economically significant 12-month hedge returns after IFRS adoption, a result that corroborates the detected forecast accuracy improvements.

An implication of this study is that the adoption of IFRS by the sample European Union countries has led to the reporting of higher quality accounting information than the information generated by the domestic GAAP of those countries. Although we only examine the predictive ability of accounting information, it is a dimension critical to users of accounting information and regulators. The out-of-sample prediction tests have provided a definitive answer to this issue and our results confirm and extend the results in Barth et al. (2012) that the adoption of IFRS increased the predictability of cash flows relative to domestic accounting standards.

The results of this study can serve as the departure for studies that will also employ out-of-sample tests to resolve conflicting findings in extant literature in general and examine other dimensions of IFRS accounting quality and economic consequences. For example, future research can do a more in-depth examination of IFRS-based working capital accruals and accounting estimates. Another extension can examine whether improvements in OOS prediction have caused desirable economic effects of IFRS adoption such as lower cost of capital and higher liquidity documented in prior studies. Future research can also use the OOS methodology to examine whether the substitution between accrual-based and real earnings management after IFRS adoption documented by previous studies has an impact on forecast accuracy after IFRS adoption.

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Table 1. Descriptive Statistics

Panel A. Country Composition of the IFRS and Benchmark Samples

Country	# of Obs.	% of the Total	Rule of Law Score	Legal Enforcement Strong = 1	Securities Regulation	Securities Regulation Strong = 1	Differences from IFRS	Differences High = 1
IFRS								
Belgium	312	2.8%	1.4	1	1.01	0	13	1
Switzerland	324	2.9%	2.0	1	1.44	0	12	1
Germany	936	8.5%	1.7	1	0.64	0	11	1
Denmark	348	3.1%	2.0	1	1.5	1	11	1
Spain	132	1.2%	1.1	0	1.49	0	16	1
Finland	492	4.5%	1.9	1	1.48	0	15	1
France	2,304	20.8%	1.3	1	1.74	1	12	1
Great Britain	3,672	33.2%	1.6	1	2.17	1	1	0
Greece	132	1.2%	0.7	0	1.15	0	17	1
Italy	312	2.8%	0.5	0	1.82	1	12	1
The Netherlands	552	5.0%	1.7	1	1.86	1	0	0
Norway	372	3.4%	2.0	1	1.29	0	7	0
Portugal	84	0.8%	1.1	0	1.66	1	13	1
Sweden	1,080	9.8%	1.8	1	1.36	0	10	1
Benchmark								
India	636	5.75%	0.1	0	2.25	1	8	0
Israel	24	0.22%	0.7	0	1.96	1	6	0
Japan	4,092	37.02%	1.4	1	1.41	0	9	1
USA	6,300	57.00%	1.5	1	2.9	1	4	0

Notes: Firm-year observations are reported by country. Since the IFRS and benchmark samples are matched, each sample consists of 11,052 firm-year observations. The rule of law scores are taken from the year 2005 data in Kaufmann et al. (2007). Legal enforcement strength index takes the value of 1 (0) if the rule of law score is at least (smaller than) 1.3, which is the median value of the rule of law scores in a group of countries we examined in the sampling process, including the EU countries and 14 other candidate benchmark countries in Compustat Global and North America. Securities regulation strength index is equal to 1 (0) when the sum of the securities regulation scores based on disclosure, liability, and enforcement from Leuz (2010) is at least (lower than) 1.5, which is the median value of the securities regulation strength index in a group of countries listed above. The differences from IFRS measure is from Bae et al. (2008), which measures the differences along 21 key accounting areas between the country's domestic accounting standards and the international accounting standards (IAS or IFRS). When the differences measure is at least (smaller than) 9, we denote the country as having high (low) differences from IFRS.

Table 1. Descriptive Statistics

Panel B. Descriptive Statistics

	The IFRS Sample			The Benchmark Sample					
Variable	Mean	Standard Deviation	Median	Mean		Standard Deviation	Median	
Pre-2005								
AT	908.1	2377.3	171.1	690.5	***	1923.8	151.1	***
EARN	0.012	0.152	0.038	0.012		0.143	0.029	***
CFO	0.079	0.14	0.092	0.07	***	0.122	0.074	***
ACCR	-0.066	0.104	-0.062	-0.058	***	0.099	-0.051	***
ΔAR	-0.002	0.083	0	-0.007	***	0.063	-0.002	***
ΔINV	-0.001	0.043	0	-0.004	***	0.043	0	
ΔAP	0.014	0.068	0.006	0.005	***	0.049	0.002	***
DP	0.058	0.039	0.051	0.045	***	0.034	0.038	***
OTHER	0.003	0.187	-0.009	0.003		0.18	-0.006	
BTM	0.909	0.874	0.675	0.997	***	1.019	0.711	*
LOGMV	4.695	1.835	4.657	4.45	***	1.907	4.393	***
Post-2005								
AT	1991.4	4970.7	343.1	1233.7	***	3496.1	250	***
EARN	0.041	0.097	0.044	0.024	***	0.117	0.034	***
CFO	0.084	0.095	0.081	0.075	***	0.104	0.075	***
ACCR	-0.043	0.077	-0.039	-0.052	***	0.089	-0.044	***
ΔAR	-0.003	0.054	-0.002	-0.007	***	0.051	-0.003	***
ΔINV	-0.003	0.033	0	-0.005	**	0.035	0	
ΔAP	0.007	0.045	0.004	0.004	***	0.04	0.002	***
DP	0.04	0.027	0.035	0.041	***	0.03	0.035	
OTHER	0.01	0.132	0.005	0.006	*	0.15	0.002	**
BTM	0.947	0.931	0.681	0.944		0.831	0.754	***
LOGMV	5.39	1.964	5.348	5.062	***	1.925	4.998	***

Notes: *AT*: total assets in millions of US dollars; *EARN*: net income before extraordinary items; *CFO*: cash flow from operations minus the accrual portion of extraordinary items; *ACCR*: accruals, defined *EARN – CFO*; *ΔAR*: change in accounts receivable; *ΔINV*: change in inventory; *ΔAP*: change in accounts payable; *DP*: depreciation and amortization; *OTHER*: other accruals, defined as *EARN – (CFO + ΔAR + ΔNV – ΔAP – DP)*; *BTM*: book to market ratio; *LOGMV*: natural logarithm of market value of equity. All variables are measured as of the end of the year. All variables except for *AT*, *BTM*, and *LOGMV* are deflated by beginning total assets. For accruals component variables *ΔAR*, *ΔINV*, *ΔAP*, when cash flow variables are missing, changes in balance sheet items are used instead. All variables are winsorized at the top and bottom one percentile of their respective distributions. There are 921 firms and altogether 11,052 observations over the 12-year period, four years pre-2005 (3,684 observations) and eight years post-2005 (7,368 observations), in each of the IFRS sample and the benchmark sample. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels respectively, for tests of mean and median differences.

Table 2. In-sample Regressions

Panel A. In-sample Prediction Regressions of $EARN_{t+1}$ and CFO_{t+1}, the IFRS Sample

Model	*Intercept*	*CFO*	*EARN*	*ACCR*	*ΔAR*	*ΔINV*	*ΔAP*	*DP*	*OTHER*	R^2	*ΔCFO/ ΔEARN (Pre-Post)*	*ΔCFO/ ΔEARN Diff.-in-Diff.*
Forecast of $EARN_{t+1}$												
Pre-2005												
1	-0.010	**0.438**								0.310		
2	0.009		**0.623**							0.476		
3	0.000	**0.669**		**0.518**						0.506		
4	0.012	**0.671**			0.391	0.436	-0.606	**-0.667**	0.465	0.577		
Post-2005												
1	-0.014	**0.571**								0.328	-0.133 ***	-0.117 ***
2	0.009		**0.649**							0.441	-0.026 ***	-0.088 ***
3	-0.005	**0.751**		**0.527**						0.504	-0.082 ***	-0.003 ***
4	0.003	**0.763**			0.261	0.395	**-0.603**	**-0.765**	**0.446**	0.571	-0.092 ***	-0.022 ***
Forecast of CFO_{t+1}												
Pre-2005												
1	**0.047**	**0.474**								0.326		
2	**0.075**		**0.479**							0.263		
3	**0.051**	**0.591**		0.242						0.385		
4	0.038	**0.625**			0.191	0.149	**-0.652**	0.049	0.275	0.525		
Post-2005												
1	**0.036**	**0.540**								0.335	-0.066 ***	0.027 ***
2	**0.061**		**0.515**							0.320	-0.036 ***	0.045 ***
3	**0.041**	**0.636**		**0.287**						0.410	-0.045 ***	0.062 ***
4	0.019	**0.638**			0.086	0.293	**-0.602**	0.231	**0.303**	0.518	-0.013 ***	0.061 ***

Notes: This table presents the in-sample regressions of year *t+1* earnings and cash flow from operations on current earnings (Model 1) and earnings components (Models 2, 3, and 4). The means of the estimated regression coefficients and R^2 of regressions run on country-year cross sections are presented; regression coefficients in bold are statistically significant at least at the 5% level. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, derived from a bootstrap distribution of the change in *CFO or EARN* and the difference-in-differences between the IFRS sample and the benchmark sample (i.e., ΔCFO or ΔEARN of the IFRS sample less ΔCFO or ΔEARN of the benchmark sample).

Table 2. In-sample Regressions

Panel B. In-sample Prediction Regressions, Dependent Variable = EARN$_{t+1}$

Year	***Intercept***	***CFO***	***ΔAR***	***ΔINV***	***ΔAP***	***DP***	***OTHER***	***R^2***
The IFRS Sample								
Pre-2005								
2000	0.024	0.523	0.250	0.199	-0.690	-0.780	0.319	0.585
2001	-0.010	0.761	0.340	0.463	-0.669	-0.666	0.494	0.597
2002	0.007	0.755	0.487	0.573	-0.527	-0.633	0.569	0.569
2003	0.025	0.644	0.486	0.509	-0.537	-0.588	0.480	0.555
Post-2005								
2006	0.045	0.640	0.428	0.405	-0.478	-0.908	0.445	0.535
2007	-0.005	0.758	0.342	0.369	-0.459	-0.814	0.416	0.523
2008	-0.027	0.726	0.054	0.182	-0.451	-0.290	0.281	0.532
2009	0.007	0.795	0.241	0.630	-0.517	-0.912	0.393	0.580
2010	-0.006	0.711	0.156	0.508	-0.513	-0.481	0.517	0.569
2011	-0.004	0.750	0.341	0.306	-0.742	-0.669	0.459	0.578
2012	0.004	0.846	0.240	0.508	-0.708	-0.984	0.543	0.607
2013	0.009	0.880	0.285	0.249	-0.955	-1.065	0.516	0.640
The Benchmark Sample								
Pre-2005								
2000	-0.011	0.536	0.259	0.270	-0.354	-0.348	0.293	0.399
2001	0.010	0.726	0.289	0.345	-0.599	-0.839	0.415	0.544
2002	0.004	0.638	0.651	0.682	-0.503	-0.353	0.589	0.512
2003	0.028	0.671	0.095	0.196	-0.455	-0.711	0.384	0.338
Post-2005								
2006	0.014	0.684	0.102	0.092	-0.474	-0.576	0.311	0.527
2007	-0.014	0.683	-0.046	0.192	-0.676	-0.880	0.368	0.377
2008	0.004	0.642	-0.179	0.161	-0.535	-0.595	0.264	0.395
2009	0.012	0.619	0.164	0.214	-0.355	-0.556	0.391	0.419
2010	-0.003	0.606	0.419	0.461	-0.192	-0.640	0.447	0.412
2011	0.014	0.687	0.483	0.433	-0.443	-0.995	0.557	0.480
2012	-0.003	0.902	0.342	0.713	-0.781	-0.982	0.622	0.616
2013	0.000	0.883	0.373	0.331	-0.943	-0.895	0.650	0.631

Notes:
Regressions using Model 4, $EARN_{t+1} = \beta_0 + \beta_1*CFO_t + \beta_2*\Delta AR_t + \beta_3*\Delta INV_t + \beta_4*\Delta AP_t + \beta_5*DP_t + \beta_6*OTHER_t + \varepsilon_t$, are run for each country-year and the averages of the regression coefficient estimates and R^2 in each year are presented, for the IFRS and benchmark samples, respectively.

Table 3. Out-of-Sample Forecast Evaluation: IFRS Sample – Forecasts of $EARN_{t+1}$ and CFO_{t+1}

Model	Forecast of $EARN_{t+1}$ MAPE (1)	Forecast of CFO_{t+1} MAPE (2)	Forecast of $EARN_{t+1}$ MPE (3)	Forecast of CFO_{t+1} MPE (4)	Forecast of $EARN_{t+1}$ RMSE (5)	Forecast of CFO_{t+1} RMSE (6)
Pre-2005						
1	0.062	0.064	0.003	-0.001	0.098	0.093
2	0.054 @	0.071 @	0.009	0.004	0.094 @	0.101 @
3	0.054 @	0.063 @,#	0.007	0.001	0.092 @	0.093 #
4	0.056 @,#,$	0.064 #,$	0.005	-0.001	0.096 @,#,$	0.094 @,#,$
Post-2005						
1	0.052	0.052	-0.004	-0.001	0.080	0.076
2	0.047 @	0.055 @	-0.002	0.000	0.077 @	0.078 @
3	0.046 @,#	0.051 @,#	-0.002	0.000	0.076 @	0.075 @,#
4	0.048 @,#,$	0.052 #,$	-0.001	0.001	0.081 @,#,$	0.076 #,$
Pre-Post						
1	0.011 ***	0.012 ***	0.007 ***	0.000	0.018 ***	0.017 ***
2	0.007 ***	0.016 ***	0.011 ***	0.004 ***	0.017 ***	0.022 ***
3	0.008 ***	0.012 ***	0.010 ***	0.001 ***	0.016 ***	0.018 ***
4	0.007 ***	0.012 ***	0.006 ***	-0.002 ***	0.015 ***	0.017 ***
Difference-in-Differences						
1	0.012 ***	0.008 ***	-0.003 ***	-0.001 ***	0.016 ***	0.012 ***
2	0.010 ***	0.012 ***	0.002 ***	0.002 ***	0.014 ***	0.015 ***
3	0.011 ***	0.009 ***	0.001 ***	0.001 ***	0.013 ***	0.010 ***
4	0.010 ***	0.007 ***	-0.001 ***	-0.001 ***	0.011 ***	0.010 ***

Notes: This table presents means of the out-of-sample prediction evaluation metrics and the comparisons of the means of these measures in the two sample periods: pre-2005 and post-2005. *MAPE:* Mean absolute prediction error; *MPE*: Mean prediction error; *RMSE:* Root mean square error. There are 921 observations each year, with three years in the Pre-2005 subsamples (2001-2003) and seven years in the post-2005 subsamples (2008-2014), for which we can construct out of sample forecasts and conduct the performance evaluation. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels respectively. Statistical significance is based on a bootstrap distribution of the corresponding measure derived following the procedures described in the text. @ Statistical significance (at the 0.05 level or better) of Model 1 compared with Model 2, Model 3 or Model 4. # Statistical significance (at the 0.05 level or better) of Model 2 compared with Model 3 or Model 4. $ Statistical significance (at the 0.05 level or better) of Model 3 compared with Model 4.

Table 4. Out-of-Sample Forecast Evaluation: High and Low Legal Enforcement IFRS Subsamples – Forecasts of $EARN_{t+1}$ and CFO_{t+1}

	Forecast of $EARN_{t+1}$				Forecast of CFO_{t+1}			
	High Legal Enforcement		Low Legal Enforcement		High Legal Enforcement		Low Legal Enforcement	
Model	MAPE (1)		MAPE (2)		MAPE (3)		MAPE (4)	
Pre-2005								
1	0.063		0.043		0.064		0.068	
2	0.055	@	0.027	@	0.071	@	0.065	@
3	0.056	@	0.029	@,#	0.063	#	0.065	@
4	0.057	@,#,$	0.031	@,#,$	0.063	#	0.066	@,#,$
Post-2005								
1	0.052		0.045		0.052		0.043	
2	0.047	@	0.034	@	0.056	@	0.044	@
3	0.046	@	0.033	@,#	0.052	#	0.043	#
4	0.049	@,#,$	0.037	@,#,$	0.052	#	0.042	@,#,$
Pre-Post								
1	0.011	***	-0.002	***	0.011	***	0.025	***
2	0.008	***	-0.007	***	0.015	***	0.021	***
3	0.009	***	-0.005	***	0.012	***	0.022	***
4	0.008	***	-0.006	***	0.011	***	0.024	***
Difference-in-Differences								
1	0.013	***	0.005	***	0.007	***	0.025	***
2	0.010	***	-0.001	***	0.011	***	0.030	***
3	0.011	***	0.001	***	0.007	***	0.025	***
4	0.012	***	-0.008	***	0.006	***	0.028	***

Notes: This table presents means of the out-of-sample MAPE and the comparisons of the means of MAPE in the two sample periods: pre-2005 and post-2005, for the high and low legal enforcement subsamples. The 14 countries in the IFRS sample are classified into low and high enforcement subsamples using the 2005 rule of law scores from Kaufmann et al. (2007), with countries having a score lower than 1.3 designated as low enforcement. *MAPE:* Mean absolute prediction error. There are 55 (866) observations each year in the low (high) legal enforcement subsamples. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels respectively. Statistical significance is based on a bootstrap distribution of the corresponding measure. @ Statistical significance (at the 0.05 level or better) of Model 1 compared with Model 2, Model 3 or Model 4. # Statistical significance (at the 0.05 level or better) of Model 2 compared with Model 3 or Model 4. $ Statistical significance (at the 0.05 level or better) of Model 3 compared with Model 4.

Table 5. Out-of-Sample Forecast Evaluation: High and Low Securities Regulation IFRS Subsamples – Forecast of $EARN_{t+1}$ and CFO_{t+1}

Model	Forecast of $EARN_{t+1}$				Forecast of CFO_{t+1}			
	High Securities Regulation		Low Securities Regulation		High Securities Regulation		Low Securities Regulation	
	MAPE		MAPE		MAPE		MAPE	
	(1)		(2)		(3)		(4)	
Pre-2005								
1	0.064		0.065		0.062		0.069	
2	0.056	@	0.060	@	0.071	@	0.072	@
3	0.055	@,#	0.060	@	0.061	@,#	0.070	@,#
4	0.057	@,#,$	0.065	#,$	0.062	#,$	0.072	@,$
Post-2005								
1	0.049		0.058		0.049		0.057	
2	0.043	@	0.055	@	0.053	@	0.059	@
3	0.043	@	0.055	@	0.049	#	0.056	@,#
4	0.045	@,#,$	0.062	#,$	0.049	#	0.060	@,$
Pre-Post								
1	0.015	***	0.007	***	0.012	***	0.013	***
2	0.013	***	0.005	***	0.018	***	0.013	***
3	0.012	***	0.005	***	0.012	***	0.014	***
4	0.012	***	0.003	***	0.012	***	0.012	***
Difference-in-Differences								
1	0.015	***	0.007	***	0.007	***	0.012	***
2	0.013	***	0.006	***	0.013	***	0.012	***
3	0.013	***	0.007	***	0.007	***	0.013	***
4	0.013	***	0.005	***	0.006	***	0.010	***

Notes: This table presents means of the out-of-sample MAPE and the comparisons of the means of MAPE in the two sample periods: pre-2005 and post-2005, for the high and low securities regulation subsamples. The 14 countries in the IFRS sample are classified into low and high securities regulation subsamples using the securities regulation index from Leuz (2010), with countries having a score lower than the median designated as low securities regulation. *MAPE:* Mean absolute prediction error. There are 315 (606) observations each year in the low (high) securities regulation subsample. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels respectively. Statistical significance is based on a bootstrap distribution of the corresponding measure. @ Statistical significance (at the 0.05 level or better) of Model 1 compared with Model 2, Model 3 or Model 4. # Statistical significance (at the 0.05 level or better) of Model 2 compared with Model 3 or Model 4. $ Statistical significance (at the 0.05 level or better) of Model 3 compared with Model 4.

Table 6. Out-of-Sample Forecast Evaluation: High and Low Difference from IFRS Subsamples – Forecast of $EARN_{t+1}$ and CFO_{t+1}

	Forecast of $EARN_{t+1}$				Forecast of CFO_{t+1}			
	High Difference		Low Difference		High Difference		Low Difference	
Model	MAPE (1)		MAPE (2)		MAPE (3)		MAPE (4)	
Pre-2005								
1	0.060		0.071		0.065		0.064	
2	0.051	@	0.067	@	0.066	@	0.079	@
3	0.051	@	0.065	@,#	0.065	#	0.064	#
4	0.057	@,#,$	0.067	@,$	0.072	@,#,$	0.065	@,#,$
Post-2005								
1	0.049		0.057		0.050		0.054	
2	0.045	@	0.051	@	0.051	@	0.060	@
3	0.045	@	0.051	@	0.050	#	0.054	#
4	0.053	@,#,$	0.052	@,#,$	0.055	@,#,$	0.053	@,#,$
Pre-Post								
1	0.011	***	0.014	***	0.015	***	0.010	***
2	0.006	***	0.016	***	0.015	***	0.019	***
3	0.006	***	0.014	***	0.015	***	0.010	***
4	0.003	***	0.014	***	0.017	***	0.012	***
Difference-in-Differences								
1	0.012	***	0.014	***	0.014	***	0.004	***
2	0.007	***	0.016	***	0.014	***	0.013	***
3	0.008	***	0.014	***	0.014	***	0.005	***
4	0.005	***	0.015	***	0.015	***	0.006	***

Notes: This table presents means of the out-of-sample MAPE and the comparisons of the means of MAPE in the two sample periods: pre-2005 and post-2005, for the high and low difference from IFRS subsamples. The 14 countries in the IFRS sample are classified into low and high difference from IFRS subsamples using the distance measure from Bae et al. (2008), with countries having a distance lower than the mean designated as low difference. *MAPE:* Mean absolute prediction error. There are 383 (538) observations each year in the low (high) differences subsample. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels respectively. Statistical significance is based on a bootstrap distribution of the corresponding measure. @ Statistical significance (at the 0.05 level or better) of Model 1 compared with Model 2 or Model 3. # Statistical significance (at the 0.05 level or better) of Model 2 compared with Model 3 or Model 4. $ Statistical significance (at the 0.05 level or better) of Model 3 compared with Model 4.

Table 7. Mean 12-month Hedge Abnormal Returns Based on the Ranking of Predicted Earnings

	Size- and B/M-adjusted hedge returns							
	Model 1		Model 2		Model 3		Model 4	
Panel A. Overall								
(1) Ranking based on predicted earnings at t+1, Pre-IFRS sample (forecast years 2002-2004)								
12-Month-ahead mean hedge return (%)	-0.1%		-7.7%	*	-4.7%		-9.9%	*
(2) Ranking based on predicted earnings at t+1, Post-IFRS sample (forecast years 2008-2014)								
12-Month-ahead mean hedge return (%)	7.1%	*	2.0%		7.7%	**	6.7%	*
Post-Pre 12-Month-ahead mean hedge return (%): (2) - (1)	7.1%		9.7%		12.4%	*	16.6%	**
Panel B. By Legal Enforcement								
(1) Ranking based on predicted earnings at t+1, Pre-IFRS Low Legal Enforcement sample (forecast years 2002-2004)								
12-Month-ahead mean hedge return (%)	14.5%		27.3%		21.9%		16.9%	
(2) Ranking based on predicted earnings at t+1, Post-IFRS Low Legal Enforcement sample (forecast years 2008-2014)								
12-Month-ahead mean hedge return (%)	-2.1%		6.1%		-0.4%		3.6%	
Post-Pre 12-Month-ahead mean hedge return (%): (2) - (1)	-16.6%		-21.2%		-22.3%		-13.2%	
(3) Ranking based on predicted earnings at t+1, Pre-IFRS High Legal Enforcement sample (forecast years 2002-2004)								
12-Month-ahead mean hedge return (%)	-0.1%		-10.1%	**	-7.0%	**	-10.2%	**
(4) Ranking based on predicted earnings at t+1, Post-IFRS High Legal Enforcement sample (forecast years 2008-2014)								
12-Month-ahead mean hedge return (%)	5.2%		0.04%		7.1%	*	5.4%	*
Post-Pre 12-Month-ahead mean hedge return (%): (4) - (3)	5.3%		10.2%	*	14.2%	***	15.5%	***

	Size- and B/M-adjusted hedge returns							
	Model 1		Model 2		Model 3		Model 4	
<u>**Panel C. By Securities Regulation**</u>								
(1) Ranking based on predicted earnings at t+1, Pre-IFRS Low Securities Regulation sample (forecast years 2002-2004)								
12-Month-ahead mean hedge return (%)	0.5%		-5.3%		-7.6%		-8.2%	
(2) Ranking based on predicted earnings at t+1, Post-IFRS Low Securities Regulation sample (forecast years 2008-2014)								
12-Month-ahead mean hedge return (%)	14.6%	***	3.5%		9.1%	**	11.3%	**
Post-Pre 12-Month-ahead mean hedge return (%): (2) - (1)	14.1%		8.8%		16.7%		19.5%	
(3) Ranking based on predicted earnings at t+1, Pre-IFRS High Securities Regulation sample (forecast years 2002-2004)								
12-Month-ahead mean hedge return (%)	0.9%		-17.2%	**	-11.3%	*	-11.1%	
(4) Ranking based on predicted earnings at t+1, Post-IFRS High Securities Regulation sample (forecast years 2008-2014)								
12-Month-ahead mean hedge return (%)	2.3%		2.1%		5.2%		4.2%	
Post-Pre 12-Month-ahead mean hedge return (%): (4) - (3)	1.4%		19.4%	**	16.5%	*	15.4%	
<u>**Panel D. By Differences from IFRS**</u>								
(1) Ranking based on predicted earnings at t+1, Pre-IFRS Low Difference sample (forecast years 2002-2004)								
12-Month-ahead mean hedge return (%)	-4.5%		-11.9%		-7.0%		-7.3%	
(2) Ranking based on predicted earnings at t+1, Post-IFRS Low Difference sample (forecast years 2008-2014)								
12-Month-ahead mean hedge return (%)	0.1%		3.4%		7.8%		4.4%	
Post-Pre 12-Month-ahead mean hedge return (%): (2) - (1)	4.6%		15.3%		14.8%		11.7%	
(3) Ranking based on actual earnings at t+1, Pre-IFRS High Difference sample (forecast years 2002-2004)								
12-Month-ahead mean hedge return (%)	2.8%		-5.0%		-5.1%		-12.0%	
(4) Ranking based on predicted earnings at t+1, Post-IFRS High Difference sample (forecast years 2008-2014)								
12-Month-ahead mean hedge return (%)	9.3%	***	2.5%		7.1%	*	7.3%	**
Post-Pre 12-Month-ahead mean hedge return (%): (4) - (3)	6.5%		7.5%		12.2%		19.3%	*

Notes: In each year from 2002-2004 and 2008-2014 we rank the sample firms based on the predicted earnings or cash flows from each of the prediction models, Model 1 through Model 4, of the year scaled by average total assets and form 10 portfolios. For each portfolio we calculate abnormal (size and book-to-market adjusted) returns over the 12-month period starting from July of the year to June of the following year. The reported abnormal return (%) for each portfolio is the mean of the yearly mean portfolio abnormal returns over the 3-year period 2001-2003 for the Pre-IFRS sample and over the 7-year period 2007-2013 for the Post-IFRS sample; hedge abnormal return (%) is defined as the difference in portfolio abnormal returns between the highest and lowest deciles. The *t*-statistics are based on the standard errors of the yearly mean portfolio returns as in Fama and MacBeth (1973). Model 1 is based on current cash flow from operations only (CFO). Model 2 is based on current net income before extraordinary items only (EARN). Model 3 is based on current cash flow from operations and accruals (CFO, ACCR). Model 4 is based on current cash flow from operations, change in accounts receivable, change in inventory, change in accounts payable, depreciation and amortization expenses, and other accruals (CFO, ΔAR, ΔINV, ΔAP, DP, OTHER).