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R&D Reporting Rule and Firm Efficiency

Abstract

US GAAP (*SFAS 2*) requires immediate expensing of research and development (R&D) expenditure. Critics of this rule contend that the current treatment incentivizes managers to cut essential investments in R&D to manage short-term profits, and such actions could lead to longer-term adverse consequences for firms and investors. While other observers argue that there is little rigorous research that suggests that the current accounting treatment has harmful consequences. In this study, we exploit a setting in Germany when the accounting rule for R&D reporting changed from immediate expensing (as in the U.S.) to partial capitalization when Germany adopted International Financial Reporting Standards (IFRS) in 2005. We analyze German public companies over the years 1997 to 2009, and employ an econometric technique called Stochastic Frontier Analysis (SFA) to generate estimates of firm-specific efficiency for each firm-year in our sample. An attractive feature of the German setting is that it enables a firm to act as its own control, and as a result, concerns regarding self selection and omitted firm attributes could largely be mitigated. We find that efficiency of German firms improved significantly in the post-IFRS adoption period relative to the pre period. We also run our tests on a *control* sample of German companies that have *never* reported R&D expense during our sample period and find no evidence of efficiency gain for this *control* group following the IFRS adoption. This analysis helps to closely tie the observed efficiency gain to the change in the R&D reporting rule. Finally, our results are robust to alternative model specifications, various alternative input and output measures for estimating efficiency, and a battery of sensitivity tests.

JEL Classifications: G15; G38; M48

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1. Introduction

In recent decades, investments in research and development (R&D) activities have grown dramatically in the United States.[1] Although companies continue to invest huge sums in R&D, the current accounting rule mandates immediate expensing of all R&D expenditures. Critics have long opined that the immediate expensing of R&D distorts managerial resource allocation decisions leading to significant costs to companies and investors (e.g., Aboody and Lev, 1998; Lev, 2001, among others). Proponents of the current accounting rule, on the other hand, argue that given the high level of uncertainty associated with the outcome of R&D investments, capitalization of R&D could lead to undesirable consequences, such as reduced earnings quality and increased agency costs (e.g., LaFond and Watts, 2008). While others observers point out that there is little rigorous research evidence to suggest that the accounting rule has any potential harmful consequence (Skinner, 2008a). Given substantial past and current investments in R&D, the outcome of this debate has important consequences for companies, investors and the U.S. economy as a whole. The purpose of this study is to shed light on this important debate by investigating whether the current accounting treatment of expensing R&D leads to longer-term firm-specific operational inefficiency.

The current accounting rule of expensing R&D is likely to depress near-term profits of a firm if investments in R&D are growing over time.[2] Since the U.S. has experienced explosive growth in investments in R&D over the last several decades, the current accounting rule is likely

[1] The ratio of R&D investments to Gross Domestic Product (GDP) in the U.S. has almost doubled from 1953 to 2003 (Wang, 2007). Leonard Nakamura of the Federal Reserve Bank of Philadelphia estimates that the value of investments in R&D was approximately $1 trillion in 2000 (Nakamura, 2001).

[2] Lev et al. (2005) point out that conservative or aggressive accounting rule essentially shifts earnings from one period to another. Thus, over the lifetime of the enterprise, if reported earnings under a conservative rule are understated during certain periods, they have to be overstated in other periods. Consequently, the current accounting rule would downwardly bias near-term profits only if the new investments in R&D depress earnings by amounts greater than the income boosts generated from reversal of old investments.

to have an overall adverse effect on near-term profitability. Several studies argue that the market fails to fully comprehend the valuation implication of the distortion of short-term profits due to the accounting rule, and as a result, firms with greater R&D expenditures are undervalued (e.g., Chan et al., 2001; Lev et al., 2005). This could induce myopic managers to reduce R&D spending to opportunistically boost short-term performance. Indeed, several empirical studies argue that their results are consistent with this notion. For example, Baber et al. (1991) contend that opportunistic reductions in R&D become more likely when the firm faces a small earnings decline or a small loss. Cheng (2004) finds that companies with CEOs who were close to retirement age showed a decrease in R&D expenditures. These studies, however, examine special settings and small and select subsets of firms. It is not clear whether evidence of temporary reduction in R&D in certain special settings and for small subsamples is sufficient to infer that the R&D reporting rule has adverse consequences for firms, such as inefficiencies in production and operation. Not surprisingly, other researchers contend that little cogent evidence exists in support of the claim that the current R&D reporting practice has dysfunctional consequences for firms. These critics further argue that the market actually functions well in valuing innovative and high technology firms (see Skinner, 2008a, 2008b).[3] Indeed, no study, to the best of our knowledge, has investigated the impact of this accounting rule on longer term firm performance. Consequently, whether or not the current accounting practice of expensing R&D leads to longer-term inefficiency remains an open empirical question.

Several difficulties make this inquiry exceptionally challenging. First, the current accounting practice has been in place for close to four decades.[4] The U.S. economy has changed fundamentally in the last four decades making it nearly impossible to compare firm performance

[3] Sections 2.2 and 2.3 describe this debate in greater details.
[4] *SFAS 2*, that mandates expensing of all R&D expenditure, was enacted in 1974. The only exception to the full expensing rule is *SFAS 86* that allows the development component of R&D of software companies to be capitalized.

in more recent time period with that from the period before the enactment of the accounting rule. Moreover, companies that invest heavily in R&D are qualitatively different from the rest of the market, and consequently, any such inquiry would likely be plagued by concerns that self selection and omitted firm characteristics are contaminating the results. What complicates the issue even further is that the objective of interest is *not* the actual R&D expenditures, but R&D outlays allegedly withheld by managers to manage short-term profits, a construct that is clearly unobservable. Interestingly, Germany offers a unique natural experiment that could shed light on the debate about the alleged harmful consequences of the R&D reporting rule in the U.S. We next briefly describe how the German setting facilitates this inquiry.

Similar to U.S. GAAP, German accounting standards used to require that all R&D expenditures should be expensed as incurred. Germany, however, adopted the International Financial Reporting Standards (IFRS) in 2005 that allows partial capitalization of R&D. International Accounting Standard (IAS) 38 mandates that while all research costs should be expensed as incurred, development expenditures should be capitalized once technological and commercial feasibilities have been established. This presents a unique opportunity to test whether or not the accounting practice of expensing R&D adversely affects future firm performance. If the accounting rule of expensing R&D incentivizes myopic managers to cut R&D in an effort to manage short-term profits, this incentive would be lower and consequently under-investment in R&D would also be lower after IFRS adoption because IFRS allows partial capitalization of R&D.

Furthermore, the partial capitalization decision could have useful signaling value. IAS 38 directs a firm to make a judgment based on all available information about the commercial feasibility of its research efforts. Once this feasibility is established and is independently vetted by an auditor, the firm may capitalize the subsequent development costs. Thus, the decision to capitalize, in this context, provides important new information to investors about the outcome of the research effort beyond just the spending on research. As a result, IAS 38 allows firms to communicate their successes in R&D projects in a credible and timely manner without having to reveal important proprietary information. Such signals could help market participants to allocate resources more efficiently. This, in turn, could enable successful managers to finance greater number of positive NPV projects at potentially lower cost of capital and enhance firm performance. Note that this line of reasoning does not presume myopic and opportunistic intentions by managers. Both arguments, however, predict an increase in operational efficiency of German firms in the post-IFRS regime. We provide relevant institutional details about the German setting in Section 2.3.

We adopt the Stochastic Frontier Analysis (SFA) approach to estimate *operational* or *technical* efficiency for a sample of German publicly traded companies over the years 1997 to 2009.[5] SFA, first proposed by Aigner, Lovell and Schmidt (1977), has been used extensively in production economics and industrial organization research. This technique estimates an efficient production frontier by enveloping the empirical data. "Best performing" companies form the efficient frontier and relatively inefficient firms reside within the frontier. The distance of an individual firm from the efficient frontier constitutes a measure of *relative* inefficiency. Using this method, we compute technical efficiency (expressed as a ratio between 0 and 1 relative to the frontier, with 1 being the most efficient) for each firm in each year during our sample period. Section 3 discusses the SFA estimation technique in details.

[5] SFA literature uses the label "technical" efficiency to describe productive efficiency of a firm given a technological regime. In this study, we use the terms "technical" efficiency and "operational" efficiency interchangeably.

We first estimate a single frontier pooling all industries together and compute efficiency estimate for each firm-year for our entire sample period. We then compare the average efficiency of each firm in the post-IFRS adoption period with its own average efficiency estimate in the pre period. An attractive feature of this research design is that a firm acts as its own control, and as a result, concerns regarding self selection and omitted firm attributes could largely be mitigated. We find strong evidence that firm-specific efficiencies improve following the IFRS adoption. This design, however, is susceptible to the criticism that the observed result could largely be driven by other accounting changes associated with IFRS adoption, and *not* attributable to the R&D rule change, *per se*. In order to address this concern, we repeat our analysis employing a *control* sample of firms that never report R&D expense during our entire 17-year sample period. Since the *control* firms do not report any R&D expenditure, they are unlikely to be materially affected by the R&D rule change, while these firms are still subject to accounting changes associated with IFRS adoption. Interestingly, we do not find any evidence of firm-specific efficiency gain from the pre to the post period for our *control* sample. This suggests that the change in the R&D reporting rule is the likely catalyst for the observed improvement in firm efficiency. We also estimate the frontier separately for each of the three R&D intensive industries for which we have sufficient data, and find qualitatively similar evidence of efficiency gains from the pre to post periods. Finally, our results are robust to two alternative model specifications, several alternative sets of input and output measures and numerous additional sensitivity tests, including a test to mitigate the concern of *event-period clustering*.[6] Taken together, our analyses suggest that partial capitalization of R&D expenditure

[6] One concern is that a macro event, otherwise unrelated but coincident to the IFRS adoption, may be driving our results. We perform a sensitivity analysis to rule out any confounding effect of such *event-period clustering*. Sections 5.5 through 5.7 describe our various sensitivity tests in details.

allowable under IAS 38 results in improvement in operational efficiency of publicly traded German firms.

Our evidence is also particularly timely and relevant because the Securities and Exchange Commission (SEC) is yet to take its final decision on whether or not the U.S. should commit to IFRS adoption. Not surprisingly, the pros and cons of IFRS adoption are being hotly debated nowadays. One of the issues that is being actively debated is the requirement to capitalize development costs under IFRS because some commentators argue that capital market performs well under the current reporting regime and mandating capitalization may simply increase costs of compliance without discernible benefits (see Skinner, 2008a, for a discussion). More generally, Ball (2010) contends that the benefits and costs of IFRS adoption are largely conjectural at this point, although scores of studies have been devoted to this topic lately. Our evidence on the effect of partial capitalization of R&D on firm efficiency, based on a unique natural experiment offered by the German setting and using a well established methodology of estimating technical efficiency, is likely to be informative to investors, standard setters and regulators in the U.S. and abroad.

The rest of the paper is organized as follows. We discuss the background literature and the German setting in Section II. Section III outlines our methodology and the research design. Section IV describes the data and our sample. Section V reports the empirical results, and finally Section VI provides concluding remarks.

2. Motivation and the German Setting

2.1. The debate on the agency cost of R&D investments

Numerous prior studies argue that the agency problem between shareholders and managers is likely to be greater when firms invest heavily in R&D, and this, in turn, could lead to long-term adverse consequences for firms. The literature puts forward the following arguments to explain why R&D investments are particularly vulnerable. First, asymmetric stock price response to good versus bad news could induce managers to overstate financial performance during their tenure (LaFond and Watts, 2008). Prior research documents that the unconditional stock price response to bad news disclosures is larger than the response to good news disclosures, on average (e.g., Skinner, 1994, among others). This could drive managers to forego certain desirable long-term investments in order to avoid short-term negative surprises. The current accounting rule of expensing all in-process R&D adversely affects near-term profitability. Consequently, managers are more likely to reduce R&D expenditures than other types of investments (investments that could be capitalized and amortized over future years, and thus, have less drastic impact on short-term profits) even when such resource allocation decisions are sub-optimal and could be detrimental to the firm, in the long run (see Hall, 2002, for an overview of this literature).[7]

Furthermore, information asymmetry between shareholders and managers is generally greater for R&D projects compared to other types of investments. Leland and Pyle (1977) contend that it is more difficult for investors to distinguish between good and bad projects when investment projects are associated with long-term R&D expenditures. Aboody and Lev (2000) argue that knowledge about R&D activity is an important source of insider information for R&D intensive firms compared to non-R&D intensive firms. Firms also like to protect the value of their proprietary knowledge and are unwilling to reveal important information about their R&D investments, thereby exacerbating information asymmetry for R&D projects (Bhattacharya and

[7] Another related argument predicting strategic under-investments in R&D is the following. Executives are risk averse because much of their reputational and human capital is tied to the performance of the firm, unlike shareholders who could diversify away, to a large extent, firm-specific risks. Thus, executive may consider R&D investments to be less desirable than other investments because R&D projects are associated with greater uncertainty and generally viewed as riskier than other investments (e.g., Chan et al., 2001; Kothari et al., 2002).

Ritter, 1983; Anton and Yao, 2002). Higher level of information asymmetry makes monitoring more costly and less effective, providing further impetus to managers to reduce desirable R&D investments to manage short-term profit goals. In summary, a large number of studies argues that the current accounting rule of expensing R&D creates perverse incentive for managers to under-invest in R&D and that could be detrimental to capital markets and firms.[8]

Some commentators, on the other hand, point out that very little rigorous empirical evidence is offered in support of the claim that the current accounting practice has adverse consequences for firms and investors. Skinner (2008a) critiques several studies that make the above claim and concludes that the results documented in these papers do not necessarily say anything about the desirability of the current accounting treatment. Instead, he asserts, the results simply reflect that R&D intensive firms have different economic characteristics (e.g., they're riskier, with larger information asymmetries) compared to other firms (Skinner, 2008a, p. 196).

There is also evidence that the market does work to partially eliminate information asymmetries associated with R&D investments. Barth et al. (2001) document that R&D intensive firms have more analyst coverage than non-R&D intensive firms. Tasker (1998) finds that R&D intensive companies conduct more conference calls compared to other firms. The market also devises innovative ways to mitigate information asymmetries and to finance high-tech research ventures. For example, venture capitalists generally take large equity positions in high-tech start-ups and play an active role in managing their operations and investments, largely mitigating information asymmetries in a way that is not possible with publicly traded equity (e.g., see Gompers, 1995). Indeed, the explosive growth of the venture capital industry to finance high-tech start-ups in Silicon Valley suggests that this approach works better than traditional equity

[8] Some observers rely on this line of reasoning to assert more broadly that overall innovation in the U.S. economy could be stifled because firms that rely on knowledge-based exploration and research activities are unduly handicapped by the current R&D disclosure rule in the U.S. (e.g., Wallman, 1995; Lev, 2003).

financing in supporting young high-tech companies. There is, however, insufficient evidence to infer whether or not the market's efforts to eliminate information asymmetries largely mitigate the agency costs associated with R&D investments.

2.2. Evidence on managerial manipulations of R&D expenditures

Our discussion, thus far, highlights the fact that the debate over the desirability and consequence of the current accounting rule of expensing R&D is far from settled. Several studies examine special settings, select sub-samples and certain characteristics of executive compensation contracts to provide evidence of opportunistic manipulations of R&D expenditures. For example, Dechow and Sloan (1991) examine a sample of firms in industries that have significant R&D activities and find that CEOs spend less on R&D during their final years in office. They, however, contend that these reductions are largely mitigated through CEO stock ownership. Bushee (1998) reports that although high institutional ownership, in general, tends to curb myopic managerial behaviors, a large proportion of ownership by institutions that have high portfolio turnover and engage in momentum trading significantly increases the likelihood that managers opportunistically reduce R&D to reverse an earnings decline. Cheng (2004) finds that firms use equity compensation to reduce opportunistic reductions in R&D outlays in situations when the CEO approaches retirement, and when the firm faces a small earnings decline or a small loss. Graham et al. (2005) survey over 400 senior executives to report that 80% would reduce discretionary expenditures on R&D, among others, in order to meet short-term earnings targets. Roychowdhury (2006) provides evidence consistent with managers strategically reducing discretionary expenditures, including R&D, to improve reported margins. Xue (2007) finds that firms that rely more on equity compensation for executives are more likely to perform R&D than firms that rely more on accounting-based compensation. Collectively, these studies provide evidence that managers tend to opportunistically under-invest in R&D in order to manipulate short-term profit goals.

It is, however, not possible to infer that the temporary reductions in R&D spending, documented in select subsets of firms and under certain special circumstances, actually render firms operationally inefficient and less competitive. The inquiry gets complicated by the fact that there is no natural event that a researcher can rely on to test the link between the current R&D disclosure rule and overall firm performance; the current accounting regime in the U.S. is in place for almost four decades. In addition, R&D-intensive companies are fundamentally different from other companies. Thus, any cross-sectional research design is susceptible to the criticisms that self selection and/or correlated omitted firm characteristics are driving the results. Interestingly, Germany offers a unique natural experiment that could be exploited to address this research question. We next describe how the German setting facilitates this inquiry.

2.3. The German setting

As mentioned earlier, German accounting principles used to require, prior to IFRS adoption, that all internally generated intangible assets, including R&D expenditures, should be expensed as incurred (§ 248 (2) HGB).[9] However, effective January 1, 2005, the European Union (EU) Council Regulation 1606/2002 made it mandatory for public companies in Germany to adopt IFRS. IFRS allows partial capitalization of R&D; while research costs are immediately expensed, *IAS 38* requires development costs to be capitalized when technological and commercial feasibilities have been established. *IAS 38* specifies six conditions and directs that all six criteria must be met before a company can claim technological and commercial feasibility. Thus, Germany offers a unique natural experiment to investigate the impact of the accounting

[9] HGB–the German Commercial Code–is the German version of the U.S. GAAP. It has been regulating the German accounting system since 1897. HGB was amended in 1985 in order to follow the European harmonization process in financial accounting (Roberts, Weetman and Gordan, 2002, p. 310).

practice of expensing R&D on longer-term firm performance. The performance of the same German firm can be tracked under two accounting regimes – one prior to the IFRS adoption when German GAAP required full expensing of R&D, and one following the IFRS adoption when partial capitalization has been mandated. This setting is useful because it allows a firm to act as its own control thereby effectively controlling for the confounding effects of various firm attributes on cost and productivity.

Although German firms were mandated to adopt IFRS from January 2005, many German firms voluntarily adopted IFRS prior to 2005. Starting from April 1998, the *KapAEG* law permits German firms to choose IFRS (then IAS), or U.S. GAAP, or German GAAP for preparing their financial reports (Leuz and Verrecchia, 2000). Further, *New Market*, launched in March 1997 as a new German stock market segment for innovative and fast growing industries, explicitly required listed German firms to prepare financial statements according to either IAS or U.S. GAAP (Leuz, 2003).[10] Leuz and Wustemann (2004) report that more than 40% of the companies in the German DAX100 index have already adopted IAS by 2004. Hung and Subramanyam (2007) find that 81 German industrial firms adopted IAS even before 2003. Not surprisingly, we also find that a sizable proportion of our sample firms proactively adopted international accounting standards prior to 2005. Consequently, we do not use 2005 as the blanket adoption year for all of our sample firms. For firms that have adopted early (hereafter, early adopters), we use the first year of voluntary adoption as the event year for our pre- post-

[10] Starting from 2003, firms listed in the *New Market* segment were being reassigned to two distinct groups called General Standard and Prime Standard. The Prime Standard firms were still required to prepare financial statements in accordance with either the IAS or the U.S. GAAP. General Standard firms, on the other hand, were allowed to revert back to HGB or the German GAAP (Leuz, 2003; Daske, 2005). We also observe in our sample that a few early adopters of IAS reverted back to German GAAP later.

adoption analysis, whereas firms that adopted IFRS only after the EU mandate (hereafter, timely adopters), we use 2005 as the adoption year.[11]

The German setting is useful for another important reason. Like the U.S., Germany is a developed industrialized nation that has a large, primarily unregulated market economy, well established democratic and capitalist institutions, and highly liquid capital markets. Germany also relies, to a large extent, on technical and knowledge-based innovations, supported by large investments in R&D, as its engine for economic growth, similar to the U.S. (Dinh et al., 2010). Further, Germany has a long tradition of the "rule of law" and an efficient judicial system ensuring prompt and adequate enforcement of accounting rules, as in the U.S. (e.g., Hung and Subramanyam, 2007). Hence, we feel that our analyses of German public companies have the potential to shed light on the important debate in the U.S. about the desirability of the current accounting rule of expensing R&D. Since the desirability of IFRS adoption has been hotly debated nowadays, inferences drawn and lessons learnt from the German experience are likely to be relevant to regulators and standard setters in the U.S.

Specifically, we investigate the following research question: "whether or not the operational efficiencies of German public companies have improved in the post IFRS-adoption period relative to the pre adoption period?" As described earlier, if the accounting rule of expensing R&D distorts managerial resource allocation decisions and leads to sub-optimal investments in R&D, we would expect that average firm-specific efficiencies should be lower in the pre-adoption period compared to the post-adoption period.[12]

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[11] The presence of a relatively large number of early adopters of IFRS in our sample of German firms enables us to undertake analysis that mitigates the concern of event time clustering. We discuss this analysis when we present our empirical results in Section 5.4.

[12] Note that we may not observe an increase in the level of R&D expenditure in the post-IFRS adoption period even if the partial capitalization rule largely eliminates opportunistic intention of under-investing in R&D. IFRS does not mandate specific disclosure of capitalized development expenditure, and consequently, it is capitalized under

3. Methodology and Research Design

3.1. Methodology

We adopt the Stochastic Frontier Analysis (SFA) approach to estimate operational efficiency for each firm-year in our sample. This estimation technique was first proposed by Aigner, Lovell and Schmidt (1977), and it has been used extensively since then in production economics, industrial organization and operations research literatures to estimate technical efficiency (e.g., Fried, Lovell and Schmidt, 1993; Lovell, 1996; Fare and Grosskopf, 1997; Coelli, Rao and Battese, 1998, among others). Since the body of accounting regulations represents a highly structured set of rules, the SFA approach seems well suited to analyze the impact of an accounting regulation on firm efficiency.

However, the SFA technique has been used relatively sparsely in the accounting literature; only a handful of accounting studies employs this estimation technique. For example, using data reported by public school districts, Dopuch and Gupta (1997) use SFA to estimate benchmark performance standards in relative performance evaluation. Dopuch et al. (2003) estimate the relative efficiency of audit production and find that inefficiencies in audit production are associated with reduced audit fees, consistent with the notion that the cost of inefficiency is being partially borne by accounting firms. Callen et al. (2005) use SFA to measure plant-level efficiency for firms that have adopted just-in-time (JIT) production. Baik et al. (2010) examine the role of SFA-based efficiency metrics in valuation of firms and benchmark these measures against more traditional accounting ratios, and find that SFA-based efficiency metric has incremental explanatory power over traditional accounting ratios.

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various different assets. Thus, the R&D spending in the pre-period is not comparable with that of the post-period because they are measured differently.

SFA is an econometric technique used to estimate an efficient production frontier based on empirical data and then use this frontier to estimate the technical efficiency of individual firms. The method assumes a relationship between the set of inputs and the output based on a production function specified *a priori* by the researcher, and estimates an efficient frontier using a parametric approach that envelopes the empirical data. The technique decomposes the error term into two components, one to account for purely random effects (white noise) and the other to account for technical inefficiency. The general model of SFA can be expressed as follows:

$$\ln q_i = \ln x_i \beta + (v_i - u_i), \quad i=1, \ldots, I \qquad (1),$$

Where, q_i is the output of the i^{th} firm;

x_i is a $(k\times 1)$ vector of the inputs used by the i^{th} firm;

v_i is random error, assumed to be i.i.d and have $N(0, \sigma_v^2)$ distribution;

u_i is a non-negative random variable assumed to account for technical inefficiency in production and is independent of v_i.[13]

SFA measures efficiency relative to a stochastic parametric frontier and generates an estimate of u_i given the distribution of errors and the variance estimates of the error components. Battese and Coelli (1995) enhance this basic model to include variables to explain the variations in technical inefficiency itself. Their model is as follows:

$$\ln q_{it} = \ln x_{it}\beta + (v_{it} - u_{it}) \qquad i = 1, 2, \ldots I; \; t = 1,2,\ldots T \quad (2),$$

$$u_{it} = z_{it}\,\delta + w_{it} \qquad (3),$$

where the subscripts *i* and *t* denote individual firm and time (year), z_{it} is a (1xm) vector of variables that are hypothesized to affect technical inefficiency, u_{it} and w_{it} are truncated normal distributions so as to ensure u_{it} is non-negative. Equations (2) and (3) are jointly estimated using maximum likelihood estimation to find the parameter values of β and δ, and to generate

[13] This is an intuitive and flexible specification used in numerous prior studies and based on a Cobb-Douglas production function. A more detailed account of the SFA methodology is provided in the Appendix.

estimates of u_{it} for each firm-year in our sample. The Battese and Coelli specification computes technical efficiency of a firm as a ratio of the firm's output over the estimated output generated by a fully efficient firm on the stochastic frontier. The value of this efficiency estimate lies between 0 (when u_{it} is infinitely large) and 1 (when u_{it} is 0, its lowest possible value).

3.2. Research design

Since there is no universally agreed upon output measure that encapsulates firm efficiency, we implement three versions of efficiency estimate, each employing a different output measure. The three output measures we use are Sales Revenue (SALE), Gross Margin (GM) and Cash Flow from Operations (CFO). In our primary analysis, the following variables comprise our input vector (x vector in Equation (2) above): Cost of Goods Sold (CGS), lagged Property, Plant and Equipment (lag_PPE), Selling, General and Administrative expenses (SG&A), the first two lags of R&D expenditure (lag_RD and lag2_RD), and a variable denoting the observation year (YEAR).[14] Our input variables are similar to the input measures employed in Baik et al. (2010) and Demerjian et al. (2011). The YEAR variable likely controls for any Hicksian temporal expansion of the frontier. The only explanatory variable associated with operational inefficiency in our design is ADOPT, an indicator variable that takes on the value of 1 in the adoption year and later years, and 0 otherwise. Thus, ADOPT and an intercept are the members of the z vector in Equation (3).

Our first test of whether R&D capitalization improves operating efficiency is to test whether the coefficient δ on ADOPT is negative and significant in the joint estimation of Equations (2) and (3). This will provide evidence that, on average, inefficiency has decreased (or efficiency has increased) in the post-adoption period across the entire pooled sample. In addition,

[14] We also estimate our models with several alternative sets of input measures and find broadly similar results. Section 5.6 describes this analysis in greater details.

we separately calculate average efficiency during the pre-adoption and post-adoption periods for each individual firm in our sample. We then calculate the firm-specific change in efficiency as the average post-period efficiency estimate of the firm minus its own average pre-period efficiency. We test the significance of the mean (median) change in efficiency using a t-test (signed-rank test). Thus, a positive and significant mean or median value would indicate that the firm has become more efficient in the post period.[15] Note that in this research design, each firm acts as its own control. An appealing feature of this design is that it effectively controls for all firm-specific attributes that are unaffected by the accounting rule change. Consequently, this design helps to alleviate the concern that the results are simply attributable to cross-sectional variations in firm characteristics.

In summary, we adopt the SFA methodology and more specifically, the Battese and Coelli (1995) joint estimation approach involving panel data to estimate operational or technical efficiency of German companies during the periods before and after IFRS adoption. We test if technical efficiency has changed from the pre period to the post period, on average, across the entire pooled sample. We also compute change in efficiency on a firm-by-firm basis and test whether the "change" series is significantly different from zero or not.

4. Data and Sample Selection

The sample selection procedure is summarized in Table 1. We begin by retrieving accounting data for publicly traded German companies from the Thomson Reuters Worldscope

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[15] Note that the joint estimation of Equations (2) and (3) is a pooled cross-sectional analysis, and a significantly negative δ indicates that the cross-sectional average *inefficiency* has decreased in the post period (i.e., the average cross-sectional *efficiency* has increased from the pre period to the post period). In contrast, the firm-specific measure obtained from the model quantifies *efficiency*. Thus, when we calculate a firm-specific "change" figure by subtracting the pre period estimate from the post period estimate for the same firm, a positive value is indicative of the firm being more *efficient* in the post period.

database for the years 1995 to 2009. We select this time period to ensure that we have sufficient firm-years in the pre and post IFRS accounting regimes for both the sub-groups – early adopters and timely adopters. Of the initial 960 firms (8,861 firm-years) for which financial statement data are available during the 1995-2009 period, we select firms with non-missing data for our major output and input variables such as SALE, CFO, CGS, SG&A, PPE etc. This reduces the number of firms (firm-years) to 744 (4,918). We further require firms to have at least three consecutive years of accounting data; this is necessary to calculate lag2_RD, which is a member of our input vector. Further, we delete firms that have never reported R&D expense during the entire 15-year period from 1995 to 2009 because these firms are unlikely to be affected by the change in the accounting treatment of R&D. We lose 368 firms and 2,311 firm-year observations as a result of the last two data restrictions. Finally, in order to calculate the firm-specific change in technical efficiency from the pre to the post period, we require that every firm in our sample has at least one observation in both the pre and the post IFRS adoption periods. Our final sample consists of 216 firms and 1,955 firm-year observations from 1997 to 2009.[16]

5. Empirical Results

5.1. Descriptive statistics

Table 2 provides descriptive statistics for our variables of interest. From panel A, it is clear that the medians are generally much lower than the means for all the input and output variables. This pattern persists in both the early adopters and the timely adopters sub-samples.

[16] Although we collect data from 1995, the sample used in our statistical tests stars from 1997 because one of our independent variables is lag2_RD. When the output is CFO, we further delete the bottom 1% of hugely negative outliers because we use log transformed input and output measures. After deleting the bottom 1%, we add a positive constant that is equal to the absolute value of the minimum of the distribution to all observations to transform the negative CFO values to positive figures. Such a transformation is order preserving and allows logarithmic operation, and has been used in prior research (Richardson et al., 1986; Ajinkya and Jain, 1989; Bhattacharya, 2001). Our inferences are unchanged when we simply eliminate negative CFO values.

Our use of log-transformed variables in all model estimations helps to mitigate the effect of this skewness. Panels B and C provide descriptive statistics for the early adopters and timely adopters sub-samples. The early adopters tend to be larger firms and have greater median values of input and output variables than the timely adopters. Compared with timely adopters, the early adopters also seem to be more homogeneous, as evidenced by lower standard deviations and smaller differences between mean and median values.

We report the efficiency measures by year in Panel D of table 2. In general, the efficiency measures based on the net measures of output (GM and CFO) are lower than the efficiency measure generated using SALE as the output measure. We do not find any obvious trends in the efficiency measures. There is also no obvious temporal trend. While one expects the efficient frontier itself to expand over time, firm-specific measures of technical efficiency do not seem to exhibit any time trend perhaps due to the fact that these measures are expressed as ratios using the "best performing" firms as the benchmark.

The major industries that make up our sample are reported in Panel E of Table 2. While 38 different industries are represented in the sample, for expositional ease, we report in the table industries with more than 10 firms. Business Services (SIC 73) has the most number of firms at 49. Only two other industries have more than 20 firms. Chemicals and Allied Products (SIC 28) has 21 firms, and Electronic and Other Electric Equipment (SIC 36) has 20 firms. This clearly limits our ability to run our analysis by industry. However, we replicate our main analysis separately for these three industries and report these results in addition to our pooled sample results.

5.2. Main analysis

Our primary test of change in efficiency involves estimating the Battese and Coelli (1995) specification, i.e., jointly estimating Equations (2) and (3).[17] As described earlier, we use three different measures of output, SALE, GM and CFO. In our base model, the x vector of Equation (2) includes the following inputs: CGS, lag_PPE, SG&A, lag_RD, lag2_RD and YEAR.[18] The z vector of Equation (3) contains an intercept term and the indicator variable, ADOPT, that takes on the value of 1 in the IFRS adoption year and later years, and 0 otherwise. As described in Section 3.2, Equations (2) and (3) are estimated jointly using maximum likelihood estimation, and a negative and significant coefficient δ on the indicator variable ADOPT indicates that the level of inefficiency is lower (efficiency is higher) in the post-adoption period than in the pre-adoption period, on average, across the pooled sample. The results from this estimation are reported in Table 3. The table reports that δ is negative and significant in all three specifications indicating that overall technical efficiency has improved significantly in the period after IFRS adoption.

Also, the Battese and Coelli (1995) specification can be used to generate an *efficiency* score for each firm in each year. As explained earlier, since this is an efficiency score, a positive and significant mean or median value would indicate that there is efficiency gain in the post-IFRS adoption period. We find from Table 3 that the mean (median) value of the firm-specific change in efficiency when output is SALE is 0.012 (0.010) and is highly significant suggesting that technical efficiency increased following the IFRS adoption. The results are similar when GM and CFO are used as output variables. We observe approximately 6-7% improvement in

[17] To mitigate the effects of outliers and data errors, all variables are winzorized at the 1% and 99% level in all our empirical analyses. However, the conclusions are unchanged when no winzorization is implemented.
[18] We also estimate our models with several alternative sets of input variables. The results based on these alternative input vectors are discussed in Section 5.6 as part of our sensitivity analysis.

efficiency from the pre-adoption period to the post-adoption period when GM and CFO are used as outputs. The improvement is more modest (about 1.5%) when SALE is used as an output measure, although the mean and median values are still highly statistically significant. Overall, the results reported in Table 3 suggest that the adoption of IFRS – that allows capitalization of the development cost – helps to improve operational efficiency of publicly traded German firms.

5.3. Analysis using firms that do not report R&D expenditure

Although we find strong evidence of efficiency gain of German public companies following the IFRS adoption, it is still not clear if the improvement in efficiency is attributable to the change in the R&D reporting rule, or to other rule changes associated with the IFRS adoption. One could even argue that convergence with global standards may have overall beneficial effects (such as lower cost of capital) that are not tied to individual rule change. In order to better tie our results to partial capitalization of R&D allowed under IAS 38, we undertake the following analysis. As Table 1 mentions, we delete firms from our main sample that have never reported R&D expense during our entire sample period from 1995 to 2009 because these firms are unlikely to be affected by the change in the accounting treatment of R&D. Consequently, if the conduit for the efficiency gain is anything other than the change in the R&D reporting rule, one would expect that this group (firms which report no R&D expenditure) would also experience improvement in technical efficiency following the IFRS adoption. Conversely, if these firms experience no improvement in efficiency from the pre to the post periods, it will be easier to tie the observed efficiency gain to the change in the R&D reporting rule. We, therefore, perform our main tests on this subset of companies.

The “no-R&D” sample consists of 107 firms (846 firm-year observations) that have never reported R&D expenses during our entire sample period (1995 to 2009) and have at least one observation in the pre- and post-adoption periods. When the output metric is CFO, we lose two firms due to missing cash flow data. The input vector for this analysis includes CGS, SGA, Lag_PPE, and YEAR, except that CGS is excluded from the input vector when the output metric is GM in order to avoid the mechanical relation between the two. We report the results from this analysis in Table 4. Again, we use the Battese and Coelli (1995) specification to estimate Equations (2) and (3) jointly and report the coefficient δ on the indicator variable ADOPT. We also compute the firm-specific change in efficiency and test whether the mean and the median values of this firm-specific change series are significantly different from zero or not. We find no evidence of efficiency gain in any of our tests. The coefficient δ is *not* negative for any of our output measures, and likewise, the mean and median values of the firm-specific change series are *never* positive. This implies that firms that are not R&D intensive experience no improvement in efficiency after the IFRS adoption. Taken together, results reported in Tables 3 and 4 indicate that the improvement in efficiency experienced by German firms after IFRS adoption is likely attributable to the change in the R&D reporting rule that allows partial capitalization.

5.4. Industry-specific analysis

Our pooled sample analysis discussed above requires estimating a single frontier for all firms in the German economy. This is a restrictive assumption since different industries likely have different input-output relationships, and pooling all industries together to estimate a single frontier clearly obscures the distinct differences across industries. We resort to estimating a single frontier because we have a fairly small number of German firms (216 companies) with all relevant data available in Worldscope for our sample period from 1995 to 2009. Consequently, we feel that it is important that we replicate our previous tests separately for each industry. However, as mentioned before, there are only three industries in our sample that have 20 or more firms. As a result, we conduct our industry-specific analysis on these three industries, and these results are reported in Table 5.[19]

First, we estimate the frontier using firms only in the Business Services industry (SIC 73), and Panel A of Table 5 reports these results. This industry has the highest number of firms (49 firms). We find that the coefficient δ on the indicator variable ADOPT in the Battese and Coelli (1995) joint test is negative and significant for all three output measures suggesting that inefficiency is lower in the post-adoption period. We also find that the mean and median values of the firm-specific change series are significantly positive for all three output measures suggesting significant improvements in efficiency, except that the mean change when SALE is the output measure is not significantly different from zero. Overall, the results reported in Panel A strongly indicate that operational efficiency of the Business Services industry in Germany has improved following the IFRS adoption.

For the Electronic and Other Electric Equipment industry (SIC 36), we find that the coefficient δ on the indicator variable ADOPT is significantly negative when the output measure is either GM or CFO, while δ is not significant when the output measure is SALE. The firm-specific change in efficiency is positive and significant for output measures SALE and GM, but not significant when the output is CFO. Thus, the results reported in Panel B, although weaker, are still broadly consistent with the notion that operational efficiency has increased in the post-adoption period for the Electronic and Other Electric Equipment industry.

Finally, Panel C reports results of estimating the frontier using firms only in the Chemicals and Allied Products (SIC 28) industry. We do not find any evidence of efficiency improvement in the post-adoption period for this industry. It is, however, important to note that

[19] All of our empirical tests, except the industry-specific analysis reported in Table 5, are based on the full sample that pools all industries together.

these tests are based on a very small sample (either 20 or 21 firms), and consequently, it is not possible to rule out *lack* of statistical power as a reason for the insignificant results.

In summary, the results from estimating the frontier separately for three different industries are broadly consistent with our previous analysis based on estimating a single frontier using all firms. We find strong evidence that efficiency has improved following the IFRS adoption for the industry with the most observations, Business Services. We also find significant results for the Electronic and Other Electric Equipment industry even though the sample size was very small, just 20 firms. For the Chemicals and Allied Products industry, none of our statistical tests (also based on a very small sample) are significant.

5.5. Analysis separately for early and timely adopters

Since German public companies were mandated to adopt IFRS reporting from 2005, one concern is that the results reported thus far could be attributable to a macro event that takes place around the same time and significantly impacts costs and productivity of German companies. Interestingly, while German firms were required to adopt IFRS in 2005, many firms voluntarily adopted IFRS earlier than 2005 (Leuz and Wustemann, 2004; Hung and Subramanyam, 2007). In fact, majority of our sample firms (approximately 55%) voluntarily adopted IFRS prior to 2005.[20] The fact that adoption years are not all clustered around 2005 alleviates, although not completely eliminates, the abovementioned concern. In order to reliably eliminate this concern of event-period clustering, we examine separately firms that adopted IFRS earlier than 2005 (early adopters) and those that adopted in 2005 (timely adopters). If we find similar results across the two sub-groups, the concern of event time clustering could be mitigated, and the results could be

[20] According to our sample, German public companies voluntarily switched to IFRS reporting starting as early as 1999. Of the voluntary early adopters, 1.5% adopted in 1999, 8.1% adopted in 2001, 8.7% adopted in 2002, 36.8% adopted in 2003 and 44.9% adopted in 2004. Surprisingly, no firm (according to our final sample after various attritions) adopted IFRS in 2000.

more directly attributable to IFRS adoption. Note that we do not re-estimate stochastic frontiers separately for these two sub-groups, rather we rely on the frontier constructed from estimating the Battese and Coelli (1995) specification over the pooled sample (i.e., the same frontier that is used to generate Table 3 results), and use the firm-specific efficiencies generated from this estimation.[21] We next compute firm-specific changes in average efficiencies from the pre to the post periods separately for the early adopters and timely adopters, and test whether the changes in technical efficiency were positive and significant for each sub-sample.

The results of this analysis are reported in Table 6. From Panel A, it is clear that the timely adopters experience increases in technical efficiency on adoption of IFRS that are statistically significant for all three output variables. The results for the early adopters are reported in Panel B. These results also show that these firms also experience increases in technical efficiency that are not just statistically significant but also very similar in magnitude to the timely adopters. These results demonstrate that our inferences are robust to concerns of event time clustering and self selection associated with the decision of early adoption.

5.6. Pseudo-event period analysis

Our approach measures technical efficiency of a firm by comparing the output produced by the firm with the output produced by "best performing" firms that reside on the efficient frontier. Clearly, productivity exhibits a strong temporal trend as firms, on average, become more productive over time and the efficient frontier expands as a result. Whether or not our measure of technical efficiency is sensitive to the temporal trend depends upon the rate of productivity gain achieved by "best performing" firms vis-à-vis the rates of improvement experienced by relatively less efficient firms. So far, we have simply included the YEAR

[21] Since these firms co-exist at the same point in calendar time, we feel that it is not appropriate to re-estimate separate stochastic frontier for each sub-sample because separate estimation would arbitrarily alter the constructions of the "efficient frontier" and the "relative technical efficiency" measures.

variable in our input vector to account for the time trend. It is, however, unclear whether this control is adequate; which begs the question as to what extent our results are simply an artifact of our inability to appropriately control for the temporal trend. In order to address this concern, we conduct what we call a "pseudo-event" period analysis. The idea is to designate a year as a pseudo-adoption year such that there is no accounting change in either the pre- or post-pseudo-adoption year. If our results are simply attributable to the liberal time trend and not to the accounting regime change – in the sense that our estimation of outputs (technical efficiencies) in later years are always greater than those in earlier years – we would expect that average efficiency improves from the pre-pseudo-event period to the post-pseudo-event period as well.

Figure 2 illustrates our designation of the pseudo-event years. For timely adopters (Panel A of Figure 2), we conduct the pseudo-event period analysis over the years 2000 to 2004 to ensure that the entire sample period falls in the pre-IFRS accounting regime. We then designate the years 2000 and 2001 as the pseudo-pre-adoption period, while the years 2002 through 2004 as the pseudo-post-adoption period.[22] For early adopters (Panel B), we select the pseudo-event period such that it lies entirely within the post-IFRS accounting regime, i.e., years 2005 to 2009. Note that early adopters are those who voluntarily adopted prior to the mandatory adoption year of 2005. We next assign the years 2005 and 2006 as the pseudo-pre-adoption period for early adopters, while the years 2007 through 2009 as the pseudo-post-adoption period for early adopters. We then pool early and late adopters together and estimate a frontier by jointly estimating Equations (2) and (3) and run tests analogous to those reported in Table 3. The results of this analysis are reported in Table 7. The table shows that the coefficient δ on the indicator variable ADOPT in the Battese and Coelli (1995) joint estimation is either positive or

[22] The length of our pseudo time period is limited by the need to have the entire period within either the actual pre-period or the actual post-period and the availability of data for extended time-periods.

insignificant. This suggests that technical efficiency either declined or remained unchanged in the post-pseudo-event period for relatively less efficient firms compared to "best performing" firms. Similar conclusion can be drawn using firm-specific changes in efficiency measures; they are either negative or insignificant. Thus, our analysis using pseudo-event periods lends further support to our main finding that partial capitalization of R&D allowed under IFRS results in improvements in operational efficiency of German firms.

5.7. Additional sensitivity tests

We run numerous sensitivity tests to ensure the robustness of our inferences. First, we redo our analysis after eliminating the years 2008 and 2009 from our sample. The years 2008 and 2009 were severe recessionary years for the global economy, including Germany. These years were characterized by several major exogenous shocks such as the credit crunch, housing and stock market crashes, severe corporate belt tightening etc. It is not at all clear how these shocks would affect our model assumptions and estimations, and so we rerun our main analysis after eliminating these two years. Panel A of Table 8 reports results of estimation after eliminating 2008 and 2009, and we find that the main tenor of our results hold.

Further, one of the characteristics of R&D investment is that, by its very nature, its effects take some time to flow into operational efficiencies. We already try to model this attribute by including lagged values of R&D in our input vector. In addition, we implement the following alternative approach. We re-estimate our models by starting the post adoption period one year after the adoption year, and untabulated results show that our inferences are unchanged by this variation.

Finally, we also re-estimate our models with several alternative sets of input vectors. In one version, we introduce a third lag of R&D as an additional input variable, and untabulated results are very similar. In another specification, instead of introducing R&D lags as unconstrained input variables, we use the R&D capitalization estimate following the Amir, Lev and Sougiannis (2003) study. Their empirical R&D capitalization estimate (RDCAP) is as follows:[23]

$$RDCAP_{it} = (0.9)\, RD_{it} + (0.7)\, RD_{it-1} + (0.5)\, RD_{it-2}.$$

Panel B of Table 8 reports the results of this specification and we find that they are completely consistent with our earlier findings. In yet another variation, we include Goodwill and Other Intangible Assets except Goodwill as additional input variables. There is further sample attrition when we introduce these additional input variables due to missing values.[24] Panel C of Table 8 shows that the results are very similar and supportive of our main inferences. In sum, these various sensitivity tests do not alter the main tenor of our results – that the partial capitalization of R&D due to the adoption of IFRS by German firms results in improved technical efficiency for these firms.

6. Conclusion

U.S. GAAP (*SFAS* 2) currently mandates expensing R&D outlays as incurred. Critics argue that this accounting treatment motivates managers to under-invest in R&D in order to manage short-term profits and this would ultimately make the company less efficient and less competitive (e.g., Lev, 2001, among others). Other observers, however, point out that there is no rigorous research evidence suggesting that the current accounting treatment has potential adverse consequences (e.g., Skinner, 2008a). Although several studies find that managers tend to

[23] We, however, feel that it is better to allow the flexibility for the data to decide the weights on the R&D lags instead of forcing a pre-specified lag structure. Hence, we use unconstrained R&D lags in our main analysis.

[24] Although the number of firms remain pretty much the same, observations per firm in the pre- and post-adoption periods are smaller for this specification.

temporarily under-invest in R&D, it is difficult to infer from the existing evidence, documented during special circumstances and for limited time periods, whether or not the current treatment has longer-term adverse consequences. In this study, we investigate whether the current accounting rule of expensing R&D actually leads to firm-specific operational inefficiency.

The current R&D reporting rule has been in place since 1974 making it difficult to address the question whether the rule adversely affects firm performance. Germany offers a unique natural setting that facilitates this inquiry. German accounting standards used to require, prior to IFRS adoption, that R&D investments should be expensed as incurred. Germany adopted IFRS from 2005 and IAS 38 requires that while research costs should be expensed as incurred, development expenditures should be capitalized once technical and commercial feasibility have been established. If the accounting rule of expensing R&D incentivizes myopic managers to cut R&D, this incentive would be lower and consequently under-investment in R&D would also be lower after the IFRS adoption. Further, the partial capitalization rule may have useful signaling value as managers could communicate their successes in R&D projects in a credible manner without having to reveal important proprietary information. This could result in more efficient resource allocations and lower cost of capital, which in turn could lead to more efficient investments and improved operating performance. Both of these arguments suggest an increase in operational efficiency of German firms in the post-IFRS disclosure regime.

We use the Stochastic Frontier Analysis (SFA) approach for estimating technical efficiency for each firm-year in our sample. We analyze a sample of German publicly traded companies over the years 1995 to 2009. We first estimate a single frontier by pooling all industries together and find that firm-specific operational efficiency has increased significantly in the post-IFRS period relative to the pre period. We next estimate the frontier separately for three most populous industries in our sample and find similar results. We also find qualitatively similar results when we estimate separately firms that adopt IFRS in 2005 and firms that voluntarily adopt IFRS prior to 2005. Finally, our results are robust to alternative model specifications and several alternative sets of input and output measures for estimating technical efficiency.

In summary, our evidence indicates that technical efficiency of German companies improved following IFRS adoption when partial capitalization of R&D has been allowed. One caveat of this inference is that our evidence is unable to directly tie the efficiency gain to the change in R&D reporting rule because other rules have also changed as a result of IFRS adoption. In order to address this concern, we run our main analysis on a group of German companies that have *never* reported R&D expense during our entire sample period from 1995 to 2009. If other rule changes associated with IFRS adoption drive our main results, we would expect that this group (firms which report no R&D) would also experience improvement in technical efficiency following the IFRS adoption. We, however, find no evidence of efficiency gain following the IFRS adoption for this subset of firms. This evidence, along with our main finding that German firms with R&D expenditure do experience improvement in efficiency after IFRS adoption, imply that the efficiency gain following IFRS adoption is likely attributable to the change in the R&D reporting rule that allows partial capitalization.

APPENDIX

Stochastic Frontier Analysis

Stochastic Frontier Analysis (SFA) is a parametric technique used to estimate an efficient production frontier based on empirical data and then use this frontier to estimate the technical efficiency of individual firms. This method involves estimating a production frontier to envelop the data using parametric techniques and a production function specified *a priori* by the researcher. The original model was proposed by Aigner and Chu (1968) and was of the following form:

$$\ln q_i = \ln x_i \beta - u_i \qquad \text{(A1)},$$

where q_i is the output for firm i and x_i is a vector of values of inputs. The term u_i is a non-negative random variable associated with technical inefficiency. The frontier is deterministic in the sense that the output is bounded from above by $\exp(\ln x_i \beta)$. This model, however, does not take into account the possibility of measurement errors and other sources of noise; all deviations from the frontier are assumed to be due to technical inefficiency. Aigner, Lovell and Schmidt (1977) proposed the following stochastic frontier production model where the efficient frontier itself is subject to stochastic perturbations:[1]

$$\ln q_i = \ln x_i \beta + (\nu_i - u_i), \; i=1, \ldots, I \qquad \text{(A2)},$$

where ν_i is a white noise random error to account for the statistical noise alluded to earlier. This is called a stochastic frontier because the output is bounded from above by the expectation of $\exp(\ln x_i \beta + \nu_i)$, which itself is a random variable.

The key features of this model and the measurement of technical efficiency are illustrated using Figure 1 which considers a simple case with one input and one output.[2] Firm A (B) produces an output level q_A (q_B) using the input level x_A (x_B). If there were no inefficiency effects, then the frontier output would be given by:

$$q_i^* = \exp(ln x_i \beta + v_i)\,, \; i = A, B.$$

[1] This general specification is based on a Cobb-Douglas production function and has been used in numerous prior studies.

[2] Our summary of the key features of SFA, including the figure, draws heavily from the Coelli, Rao and Battese (1998) text. Please refer to the text for more details.

Note that in Figure 1, the stochastic frontier lies above the deterministic frontier for firm A, while it lies below the deterministic frontier for firm B. This implies that if A were fully efficient, its actual output would have been above the deterministic frontier. However, even if B were fully efficient, its output would lie below the deterministic frontier due to the noise component. The figure also illustrates that if a firm is inefficient, the inefficiency component could be more or less than its distance from the deterministic frontier. The measure of technical efficiency (TE) of a firm is expressed as a ratio of the firm's output over the estimated output generated by a fully efficient firm on the stochastic frontier:

$$TE_i = \frac{q_i}{\exp(\ln x_i \beta + \nu_i)} = \frac{\exp(\ln x_i \beta + (\nu_i - u_i))}{\exp(\ln x_i \beta + \nu_i)} = \exp(-\ u_i).$$

This measure of technical efficiency takes a value between 0 and 1 and measures the output of the i^{th} firm relative to the output that could be produced by a fully efficient firm using the same input vector. Battese and Coelli (1995) generalize this approach to a panel data set where the inefficiency, u_i, can depend on a set of environmental factors (e.g., adopting a new accounting rule as in our case) and generate the maximum likelihood estimator for the panel. This leads to the following specification (outlined as Equations (2) and (3) in Section 3.1 of the paper):

$$\ln q_{it} = \ln x_{it}\beta + (v_{it} - u_{it}) \qquad i = 1, 2, \ldots I;\ t = 1,2,\ldots T \qquad \text{(A3)},$$

$$u_{it} = z_{it}\delta + w_{it} \qquad \text{(A4)}.$$

Maximum likelihood estimation is used to jointly estimate the above two equations and to generate estimates of the parameters β and δ as well as estimates of technical efficiency of $\exp(-u_i)$ for each firm-year in our sample. As mentioned earlier, the disturbance ν_i is a pure white noise term, $N(0, \sigma_v^2)$. The disturbance w_i is modeled as a truncated normal distribution, distributed as $N(0, \sigma_w^2)$ before truncation, and truncated at $-z_{it}\delta$. Note that this distributional assumption of w_i ensures that u_i is also a truncated normal distribution, distributed as $N(z_i\delta, \sigma_u^2)$ before truncation and truncated at 0. In other words, the distributional assumption of w_i is chosen to make sure that u_i is a non-negative random variable.

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Figure 1

Technical Inefficiency in a Stochastic Efficient Frontier

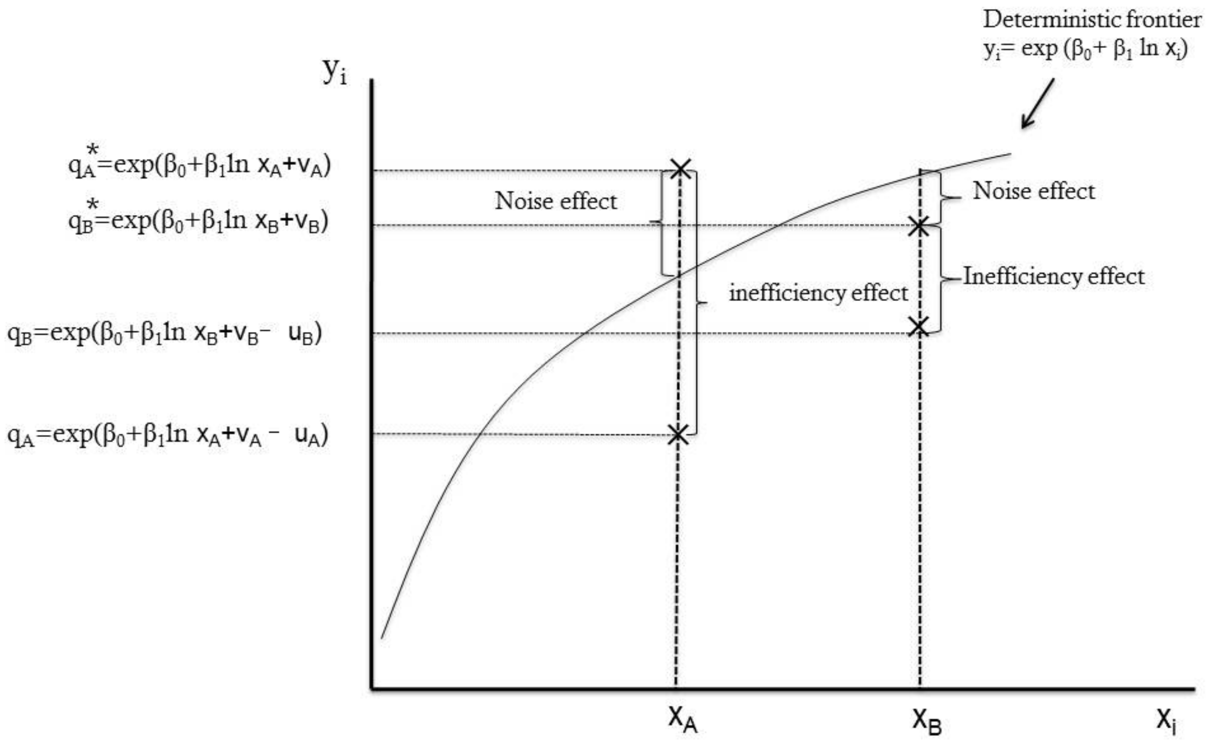
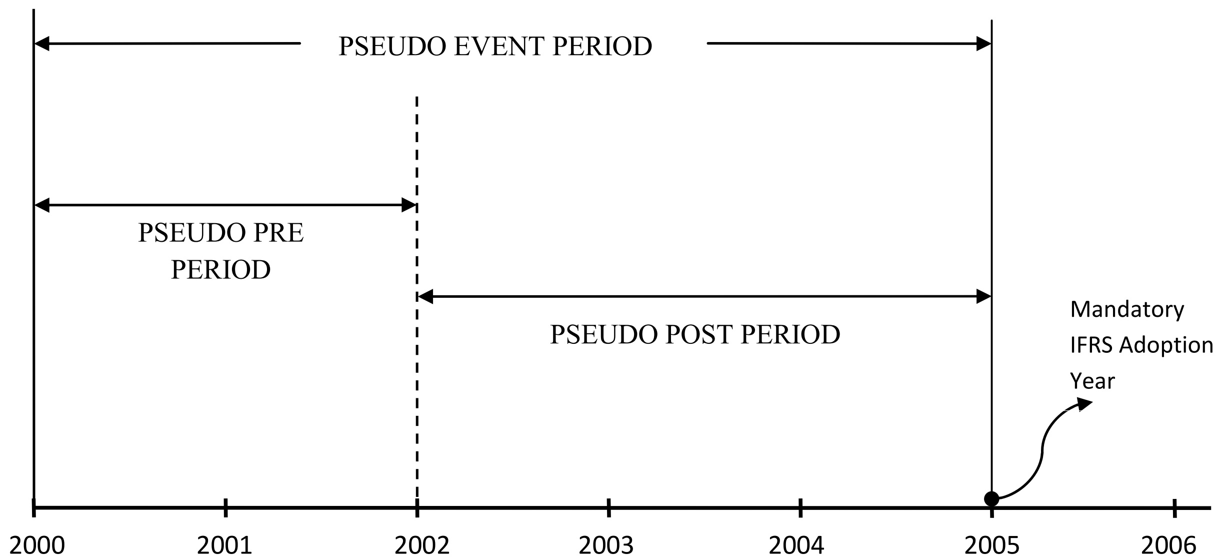


Figure 2

Pseudo Event Periods for Timely and Early Adopters

Panel A: Timely Adopters



Panel B: Voluntary Early Adopters

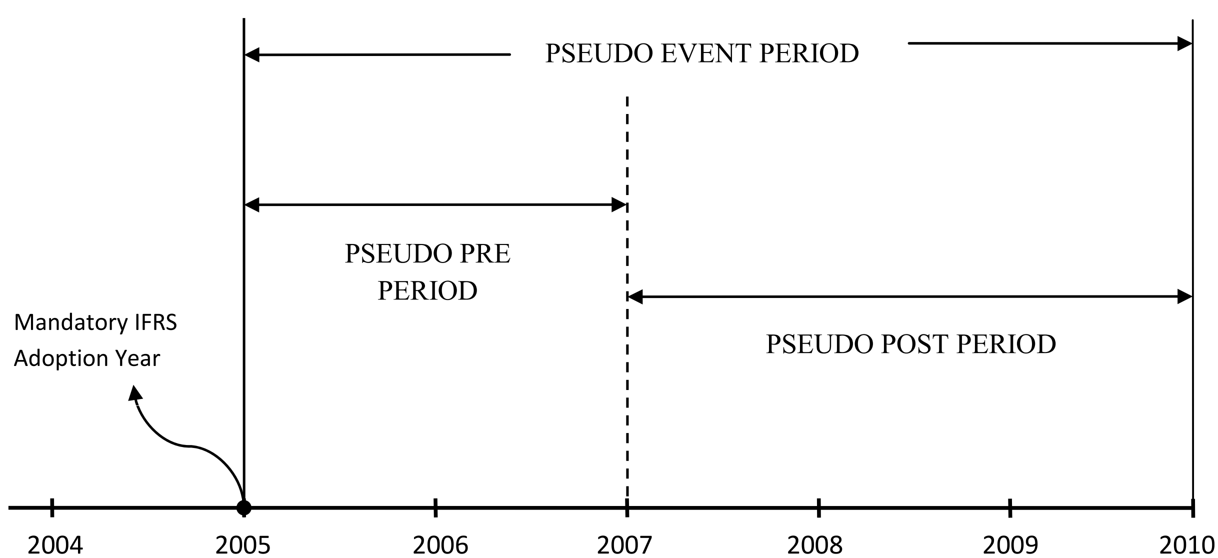


Table 1

Sample Selection

Sample Selection Procedure	Number of Firms	Firm-Years
Publicly traded German firms with financial statement data available in Worldscope database during the period, 1995-2009	960	8,861
Observations with missing data on Sales (SALE), Cost of Goods Sold (CGS), and Selling, General and Administrative Expenses (SGA)	(216)	(3,943)
Observations that do not have at least three consecutive years of data for calculating lagged values of certain input variables.	(23)	(658)
Firms that never reported R&D expenditure during our entire sample period from 1995 to 2009.	(345)	(1,653)
Firms that do not have at least 1 observation both before and after the IFRS adoption year.	(160)	(652)
Final Sample	216	1,955

When the output is cash flow from operations (CFO), we further delete firm-years with missing CFO and the bottom 1% of the remaining sample (all with negative CFOs) to facilitate log transformation. This results in a final sample of 211 firms when the output metric is CFO. We employ the sample described in Table 1 for our primary analysis where we pull all industries together for estimating a single frontier to operationalize the Battese and Coelli (1995) joint estimation.

Table 2
Descriptive Statistics

Panel A: Full Sample

Variables	Firm-Years	Mean	Median	Standard Deviation
Output Metric				
SALE	1,955	5,711	223	17,169
GM	1,955	1,777	69	5,289
CFO	1,898	629	14	2,116
Input Vector				
CGS	1,955	3,934	147	12,326
SGA	1,955	985	44	3,035
Lag_PPE	1,955	2,106	35	7,907
Lag_RD	1,955	177	3.90	692
Lag2_RD	1,955	170	2.85	684

Panel B: Early Adopters

Variables	Firm-Years	Mean	Median	Standard Deviation
Output Metric				
SALE	1,076	3,793	298	8,912
GM	1,076	1,151	98	2,837
CFO	1,060	388	17	1,202
Input Vector				
CGS	1,076	2,641	196	6,500
SGA	1,076	621	53	1,531
Lag_PPE	1,076	1,169	36	3,801
Lag_RD	1,076	96	4.23	370
Lag2_RD	1,076	89	3.40	348

Panel C: Timely Adopters

Variables	Firm-Years	Mean	Median	Standard Deviation
Output Metric				
SALE	879	8,060	171	23,426
GM	879	2,543	58	7,165
CFO	838	933	12	2,856
Input Vector				
CGS	879	5,517	110	16,788
SGA	879	1,429	41	4,156
Lag_PPE	879	3,254	34	10,911
Lag_RD	879	275	3.12	939
Lag2_RD	879	268	2.49	935

Panel D: Distribution of Technical Efficiency measures by year

		Output: SALE		Output: GM		Output: CFO	
Year	Firm-Years*	Mean	Median	Mean	Median	Mean	Median
1997	41 (34)	0.883	0.877	0.759	0.762	0.719	0.737
1998	69 (61)	0.885	0.884	0.763	0.776	0.740	0.746
1999	77 (71)	0.887	0.886	0.768	0.779	0.732	0.753
2000	101 (96)	0.895	0.888	0.790	0.794	0.692	0.739
2001	144 (140)	0.873	0.885	0.735	0.785	0.743	0.763
2002	181 (177)	0.872	0.881	0.738	0.771	0.751	0.763
2003	199 (198)	0.876	0.884	0.746	0.777	0.760	0.775
2004	202 (199)	0.886	0.892	0.776	0.803	0.775	0.792
2005	205 (201)	0.884	0.895	0.792	0.821	0.799	0.808
2006	195 (193)	0.888	0.897	0.804	0.825	0.792	0.803
2007	187 (183)	0.887	0.900	0.797	0.837	0.801	0.809
2008	181 (177)	0.890	0.900	0.804	0.834	0.788	0.804
2009	173 (168)	0.884	0.896	0.791	0.826	0.804	0.820

Panel E: Distribution of sample industries†

Industry (classified by 2-digit SIC code)	Number of firms
28: Chemicals and Allied Products	21
35: Industrial Machinery and Equipment	19
36: Electronic & Other Electric Equipment	20
37: Transportation Equipment	10
38: Instruments and Related Products	19
73: Business Services	49

* When the output metric is Cash flow from Operations (CFO), we further delete firm-years with missing CFO and the bottom 1% of the remaining sample (all with negative CFOs) to facilitate log transformation. This causes the number of observations when the output is CFO to be different each year from firm-year observations obtained for output metrics SALE and GM. The numbers reported in parentheses are firm-year observations in each year when the output metric is CFO.

†38 industries (classified by 2-digit SIC code from 01 to 99) are represented in the sample. In order to avoid clutter, only industries with more than 10 sample firms (5% of the total sample firms) are reported here. We further require a firm to be in the same industry both before and after the IFRS adoption to facilitate comparison of efficiencies in the industry-level analysis.

Variable Definitions:

SALE: Net sales or revenues as reported in WorldScope, defined as gross sales and other operating revenue less discounts, returns and allowances.

GM: Gross margin, defined as sales revenue (SALE) minus cost of goods sold (CGS).

CFO: Net cash flow from operating activities as reported in WorldScope, defined as the net cash receipts and disbursements resulting from the operations of the company.

CGS: Cost of goods sold as reported in WorldScope.

SGA: Selling, general and administrative expenses as reported in WorldScope, defined as expenses not directly attributable to the production process but relating to selling, general and administrative functions. It includes expenses such as advertising expenses and sales commissions.

Lag_PPE: One-year lagged value of the net property, plant and equipment as reported in WorldScope.

Lag_RD: one-year lagged value of the research & development expense as reported in WorldScope.

Lag2_RD: two-year lagged value of the research & development expense as reported in WorldScope.

Table 3

Comparison of Operational Efficiency before and after IFRS Adoption for the Full Sample

Output Metric	Firm-specific change in efficiency (Post-IFRS adoption estimate minus pre-IFRS adoption estimate)					Battese & Coelli (1995) joint estimation
	Number of firms	Mean of firm-specific change series	Median of firm-specific change series	t-test of Mean (p-value)	Signed-rank test of Median (p-value)	Coefficient δ (t-statistic)
SALE	216	0.012	0.010	2.68 (0.004)	5123 (<0.0001)	-0.39 (-2.66)
GM	216	0.063	0.055	8.03 (<0.0001)	7956 (<0.0001)	-5.03 (-8.96)
CFO	211	0.052	0.040	11.53 (<0.0001)	9692 (<0.0001)	-5.75 (-2.60)

A sample of 216 firms and 1,955 firm-year observations are used to estimate the frontier when the output metrics are SALE and GM, while 211 firms and 1,898 firm-year observations are used when the output metric is CFO. The input vector includes CGS, SGA, Lag_PPE, Lag_RD, Lag2_RD and YEAR, except that CGS is excluded from the input vector when the output metric is GM in order to avoid the mechanical relation between the two. The YEAR variable contains the sample fiscal year and is included to control for any Hicksian temporal expansion of the frontier. All other variables are defined in Table 2.

Battese and Coelli (1995) approach is a pooled, cross-sectional regression that jointly estimates Equations (2) and (3) specified in Section 3.1. The z vector in Equation (3) contains only the indicator variable ADOPT, that takes the value of 1 in the adoption year and later years, and 0 otherwise. δ is the coefficient on ADOPT. We also compute average efficiency separately for the pre-adoption and post-adoption periods for each firm in our sample. We next calculate change in efficiency for each firm as the average post-period efficiency estimate of the firm minus its own average pre-period estimate. The table reports the mean and the median values of these firm-specific change series.

Table 4

Comparison of Operational Efficiency before and after IFRS Adoption for the "No-R&D" Sample

Output Metric	Firm-specific change in efficiency (Post-IFRS adoption estimate minus pre-IFRS adoption estimate)					Battese & Coelli (1995) joint estimation
	Number of firms	Mean of firm-specific change series	Median of firm-specific change series	t-test of Mean (p-value)	Signed-rank test of Median (p-value)	Coefficient δ (t-statistic)
SALE	107	-0.003	-0.002	-0.81 (0.42)	-524 (0.25)	0.23 (1.75)
GM	107	-0.025	-0.021	-2.28 (0.02)	-941 (0.003)	2.80 (4.00)
CFO	105	-0.020	-0.012	-3.09 (0.003)	-1895 (<0.0001)	1.49 (4.37)

The No-R&D sample consists of 107 firms (846 firm-year observations) that have *never* reported R&D expenses during our sample period (1995-2009) and have at least 1 observation both before and after the IFRS adoption year. When the output metric is CFO, we lose two firms due to missing data on CFO. The input vector includes CGS, SGA, Lag_PPE, and YEAR, except that CGS is excluded from the input vector when the output metric is GM in order to avoid the mechanical relation between the two. The YEAR variable contains the sample fiscal year and is included to control for any Hicksian temporal expansion of the frontier. All other variables are defined in Table 2.

Battese and Coelli (1995) approach is a pooled, cross-sectional regression that jointly estimates Equations (2) and (3) specified in Section 3.1. The z vector in Equation (3) contains only the indicator variable ADOPT, that takes the value of 1 in the adoption year and later years, and 0 otherwise. δ is the coefficient on ADOPT. We also compute average efficiency separately for the pre-adoption and post-adoption periods for each firm in our sample. We next calculate change in efficiency for each firm as the average post-period efficiency estimate of the firm minus its own average pre-period estimate. The table reports the mean and the median values of these firm-specific change series.

Table 5
Industry-Specific Comparison of Operational Efficiency before and after IFRS Adoption

Panel A: Business Services (2-digit SIC code is 73)

Output Metric	Firm-specific change in efficiency (Post-IFRS adoption estimate minus pre-IFRS adoption estimate)					Battese & Coelli (1995) joint estimation
	Number of firms	Mean of firm-specific change series	Median of firm-specific change series	t-test of Mean (p-value)	Signed-rank test of Median (p-value)	Coefficient δ (t-statistic)
SALE	49	0.021	0.036	1.42 (0.16)	385 (<0.0001)	-1.98 (-2.08)
GM	49	0.064	0.070	3.50 (0.001)	416 (<0.0001)	-5.19 (-2.65)
CFO	49	0.075	0.057	5.99 (<0.0001)	529 (<0.0001)	-5.56 (-3.83)

Panel B: Electronic & Other Electric Equipment (2-digit SIC code is 36)

Output Metric	Firm-specific change in efficiency (Post-IFRS adoption estimate minus pre-IFRS adoption estimate)					Battese & Coelli (1995) joint estimation
	Number of firms	Mean of firm-specific change series	Median of firm-specific change series	t-test of Mean (p-value)	Signed-rank test of Median (p-value)	Coefficient δ (t-statistic)
SALE	20	0.049	0.035	4.92 (<0.0001)	102 (<0.0001)	-2.10 (-0.70)
GM	20	0.061	0.049	2.34 (0.03)	70 (0.007)	-5.23 (-3.97)
CFO	20	0.020	0.030	0.64 (0.53)	26 (0.35)	-3.61 (-1.75)

Panel C: Chemicals and Allied Products (2-digit SIC code is 28)

Output Metric	Firm-specific change in efficiency (Post-IFRS adoption estimate minus pre-IFRS adoption estimate)					Battese & Coelli (1995) joint estimation
	Number of firms	Mean of firm-specific change series	Median of firm-specific change series	t-test of Mean (p-value)	Signed-rank test of Median (p-value)	Coefficient δ (t-statistic)
SALE	21	-0.023	-0.023	-1.25 (0.23)	-42 (0.15)	4.26 (1.44)
GM	21	-0.0005	0.017	-0.026 (0.98)	14 (0.65)	4.34 (2.69)
CFO	20	-0.015	-0.034	-0.55 (0.59)	-36 (0.19)	1.83 (0.28)

A separate frontier is estimated for each industry. The input vector includes CGS, SGA, Lag_PPE, Lag_RD, Lag2_RD and YEAR, except that CGS is excluded from the input vector when the output metric is GM in order to avoid the mechanical relation between the two. The YEAR variable contains the sample fiscal year and is included to control for any Hicksian temporal expansion of the frontier. All other variables are defined in Table 2.

Battese and Coelli (1995) approach is a pooled, cross-sectional regression that jointly estimates Equations (2) and (3) specified in Section 3.1. The z vector in Equation (3) contains only the indicator variable ADOPT, that takes the value of 1 in the adoption year and later years, and 0 otherwise. δ is the coefficient on ADOPT. We also compute average efficiency separately for the pre-adoption and post-adoption periods for each firm in our sample. We next calculate change in efficiency for each firm as the average post-period efficiency estimate of the firm minus its own average pre-period estimate. The table reports the mean and the median values of these firm-specific change series.

Table 6

Separate Analysis for Timely Adopters and Early Adopters

Panel A: Timely Adopters (firms adopting IFRS in 2005)

Output Metric	Firm-specific change in efficiency (Post-IFRS adoption estimate minus pre-IFRS adoption estimate)				
	Number of firms	Mean of firm-specific change series	Median of firm-specific change series	t-test of Mean (p-value)	Signed-rank test of Median (p-value)
SALE	99	0.012	0.012	1.39 (0.08)	1185 (<0.0001)
GM	99	0.061	0.057	5.29 (<0.0001)	1720 (<0.0001)
CFO	96	0.053	0.040	7.27 (<0.0001)	1980 (<0.0001)

Panel B: Early Adopters (firms adopting IFRS before 2005)

Output Metric	Firm-specific change in efficiency (Post-IFRS adoption estimate minus pre-IFRS adoption estimate)				
	Number of firms	Mean of firm-specific change series	Median of firm-specific change series	t-test of Mean (p-value)	Signed-rank test of Median (p-value)
SALE	117	0.012	0.008	2.88 (0.002)	1383 (<0.0001)
GM	117	0.065	0.050	6.03 (<0.0001)	2288 (<0.0001)
CFO	115	0.052	0.041	9.06 (<0.0001)	2629 (<0.0001)

Firms that switched to IFRS in 2005 are labeled as Timely Adopters, while firms that voluntarily switched to IFRS prior to 2005 are labeled as Early Adopters. We do not re-estimate stochastic frontiers separately for these two sub-groups, rather we rely on the frontier constructed from estimating the Battese and Coelli (1995) specification over the full sample specified in Table 1, and use the firm-specific efficiencies generated from this estimation. We next calculate change in efficiency for each firm as the average post-period efficiency estimate of the firm minus its own average pre-period estimate. Panel A reports the mean and the median values of the firm-specific change series only for Timely Adopters, while Panel B reports the same just for Early Adopters. Input and output variables are defined in the earlier tables.

Table 7

Pseudo Time Period Analysis

Output Metric	Firm-specific change in efficiency (Post-IFRS adoption estimate minus pre-IFRS adoption estimate)					Battese & Coelli (1995) joint estimation
	Number of firms	Mean of firm-specific change series	Median of firm-specific change series	t-test of Mean (p-value)	Signed-rank test of Median (p-value)	Coefficient δ (t-statistic)
SALE	172	0.0017	-0.0024	0.35 (0.73)	-1480 (0.01)	-0.12 (-1.49)
GM	172	-0.039	-0.033	-4.90 (<0.0001)	-4480 (<0.0001)	3.56 (4.25)
CFO	170	-0.034	-0.030	-6.24 (<0.0001)	-5395 (<0.0001)	3.65 (2.93)

This table reports analysis where instead of IFRS adoption year being the event year, we assign a pseudo-adoption year for each firm in such a way so that there is no accounting regime change in either the pre-pseudo adoption or post-pseudo adoption periods. We designate pseudo-event years as follows. For timely adopters, we conduct the pseudo-event period analysis over the years 2000 to 2004 to ensure that the entire sample period falls in the pre-IFRS accounting regime. We then designate the years 2000 and 2001 as the pseudo-pre-adoption period, while the years 2002 through 2004 as the pseudo-post-adoption period. For early adopters, we select the pseudo-event period such that it lies entirely within the post-IFRS accounting regime, i.e., years 2005 to 2009. We next assign the years 2005 and 2006 as the pseudo-pre-adoption period for early adopters, while the years 2007 through 2009 as the pseudo-post-adoption period for early adopters. We then pool early and late adopters together and estimate a frontier by jointly estimating Equations (2) and (3) and run tests analogous to those reported in Table 3. Estimation procedure and input and output measures are defined in earlier tables.

Table 8
Sensitivity Analyses

Panel A: Efficiency estimation after eliminating years 2008 and 2009

Output Metric	Firm-specific change in efficiency (Post-IFRS adoption estimate minus pre-IFRS adoption estimate)					Battese & Coelli (1995) joint estimation
	Number of firms	Mean of firm-specific change series	Median of firm-specific change series	t-test of Mean (p-value)	Signed-rank test of Median (p-value)	Coefficient δ (t-statistic)
SALE	214	0.007	0.008	1.93 (0.054)	5571 (<0.0001)	-0.40 (-2.49)
GM	214	0.066	0.051	8.47 (<0.0001)	8483 (<0.0001)	-5.25 (-5.30)
CFO	209	0.052	0.040	11.50 (<0.0001)	9716 (<0.0001)	-5.60 (-3.71)

Panel B: Estimation based on Amir, Lev and Sougiannis (2003) R&D capitalization formula

Output Metric	Firm-specific change in efficiency (Post-IFRS adoption estimate minus pre-IFRS adoption estimate)					Battese & Coelli (1995) joint estimation
	Number of firms	Mean of firm-specific change series	Median of firm-specific change series	t-test of Mean (p-value)	Signed-rank test of Median (p-value)	Coefficient δ (t-statistic)
SALE	216	0.009	0.008	2.39 (0.018)	5622 (<0.0001)	-0.43 (-3.20)
GM	216	0.065	0.055	8.18 (<0.0001)	8070 (<0.0001)	-5.27 (-6.37)
CFO	211	0.039	0.029	9.01 (<0.0001)	8400 (<0.0001)	-4.52 (-2.39)

Panel C: Estimation using Goodwill and Other Intangible Assets excluding Goodwill as additional input variables

Output Metric	Firm-specific change in efficiency (Post-IFRS adoption estimate minus pre-IFRS adoption estimate)					Battese & Coelli (1995) joint estimation
	Number of firms	Mean of firm-specific change series	Median of firm-specific change series	t-test of Mean (p-value)	Signed-rank test of Median (p-value)	Coefficient δ (t-statistic)
SALE	215	0.013	0.011	2.81 (0.0055)	5199 (<0.0001)	-0.22 (-1.66)
GM	215	0.067	0.055	8.13 (<0.0001)	7648 (<0.0001)	-5.17 (-6.38)
CFO	210	0.021	0.020	3.56 (0.0005)	3961 (<0.0001)	-3.87 (-3.38)

Panel A reports estimation results after eliminating the years 2008 and 2009; input and output measures are defined in earlier tables. Panel B reports results from a specification that uses the R&D capitalization formula specified in the Amir, Lev and Sougiannis (2003) study instead of including R&D lags as unconstrained input variables. R&D capitalization estimate (RDCAP) is defined as follows:

$$RDCAP_{it} = (0.9)\ RD_{it} + (0.7)\ RD_{it-1} + (0.5)\ RD_{it-2}.$$

Finally, Panel 3 reports results where Goodwill and Other Intangible Assets excluding Goodwill are introduced as additional input variables. Observations with negative Goodwill or negative Other Intangible Assets are deleted.