R&D Reporting Rule and Firm Efficiency

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ABSTRACT

We examine whether the R&D reporting rule that requires expensing of R&D as incurred leads to longer-term operational inefficiency for firms. In Germany, the R&D reporting rule changed from immediate expensing to partial capitalization when Germany adopted IFRS in 2005. We examine the same German firms before and after the IFRS adoption. The German setting and the design of using each firm as its own control likely mitigate concerns regarding self-selection and omitted firm attributes. We employ Stochastic Frontier Analysis and Data Envelopment Analysis to generate firm-specific efficiency measures. We find that efficiency of German firms improved significantly in the post-IFRS period relative to the pre period. We, however, find no evidence of efficiency gains for a *control* sample of companies that have never reported R&D. Our results are robust to a battery of sensitivity tests suggesting that partial capitalization of R&D is the likely catalyst for the efficiency improvement.

JEL Classifications: G15; G38; M48

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1. Introduction

The current accounting rule in the U.S. (*SFAS 2*) requires that firms expense all research and development (R&D) expenditures as they are incurred. Critics have long opined (e.g., Aboody and Lev, 1998; Lev, 2001; Lev, 2003, among others) that the current accounting rule of immediately expensing R&D depresses near-term profits, thus incentivizing myopic managers to cut necessary investments in R&D to boost short-term earnings.[1] This could lead to strategic under-investment in R&D at significant costs to companies, investors and the U.S. economy as a whole. However, empirical evidence on the effect of the R&D disclosure rule on longer-term firm performance seems extremely sparse. Given the explosive growth in R&D investments in the U.S. in recent decades, such evidence would be informative to managers, investors and standard setters.[2] In this study, we investigate whether or not the current R&D reporting rule impairs longer-term firm-specific operational efficiency by examining a shift in the accounting regime in Germany from immediate expensing to partial capitalization of R&D.

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, Lakonishok and Sougiannis, 2001; Lev et al., 2005). This could induce myopic managers to reduce R&D spending to opportunistically boost near-term performance. Indeed, several empirical studies argue that their results are consistent with this notion: Baber et al. (1991) contend that managers reduce R&D when firms face a small earnings decline or 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, and it is not clear

[1] Lev, Sarath and Sougiannis (2005) point out that a conservative accounting rule essentially shifts earnings from one period to another. Thus, over the lifetime of the enterprise, if reported earnings are understated during certain periods, they must be overstated in other periods. Hence, 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. Consequently, the current rule would adversely impact near-term profits if investments in R&D are growing over time. Since the U.S. has experienced substantial growth in R&D investments in recent decades, the current accounting rule would adversely affect near-term profitability.

[2] 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).

whether evidence of temporary reduction in R&D for small and select sub-samples is sufficient to infer that the R&D reporting rule has longer-term adverse consequences. Furthermore, Skinner (2008) argues that little cogent evidence exists in support of the claim that the current R&D reporting rule has dysfunctional consequences for firms. Consequently, whether or not the current accounting practice leads to longer-term firm-specific inefficiency remains an open question**.**

Several difficulties make this inquiry quite challenging. First, the current accounting practice has been in place since 1974.[3] The U.S. economy has changed fundamentally in the last four decades making it nearly impossible to compare current firm performance with performance prior to 1974. Second, companies that invest heavily in R&D differ fundamentally from the rest of the market, so any such inquiry would likely be plagued by concerns that self-selection and omitted firm characteristics contaminate the results. Third, the issue is *not* the actual R&D expenditures, but R&D outlays managers forego to manage short-term profits, a construct that is clearly unobservable. The German setting and the methodologies we employ to quantify operational efficiency allow us to address these challenges.

Similar to the U.S. GAAP, German accounting standards used to require firms to expense all R&D expenditures as incurred. However, in 2005 Germany adopted the International Financial Reporting Standards (IFRS) that allows partial capitalization of R&D. International Accounting Standard (*IAS*) *38* mandates that while firms must expense all research costs as incurred, they must capitalize development expenditures once technological and commercial feasibilities have been established. If expensing R&D incentivizes myopic managers to cut R&D to manage short-term profits, this incentive would be lower, and consequently under-investment in R&D would also likely be lower after IFRS adoption because IFRS allows partial capitalization. If *IAS 38* is capable of at least partially mitigating the under-investment problem, one would expect that the efficiency of German firms would increase in the post-IFRS regime.[4]

[3] *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.
[4] An alternative view (Kanodia et al., 1989 and Seybert, 2010) suggests that if full capitalization of R&D is mandated, managers' reputational concern would result in over-investment in R&D projects already underway. This argument, however, is constructed in the context of full capitalization. So, it is unclear to what extent it is relevant for a partial capitalization disclosure regime.

Furthermore, partial capitalization may have useful signaling value. *IAS 38* directs a firm to make a capitalization judgment based on all available information about the commercial feasibility of its research efforts, and this feasibility is subject to independent vetting by auditors. Thus, the capitalization decision allows managers to credibly signal their successes in R&D projects and to reveal their beliefs that sufficient future economic benefits will be generated to recover the development costs. Since such new signals helps reduce information asymmetry and cost of capital (Aboody and Lev, 1998; Givoly and Shi, 2008), managers are able to finance a greater number of efficiency-enhancing R&D projects than when they are financially constrained. Note that this line of reasoning does not presume opportunistic managerial intentions, but predicts that operational efficiency of German firms would improve after IFRS adoption.

In order to address our research question, we measure firm-specific operational efficiency for a sample of German publicly traded companies over the years 1995 to 2011. We adopt two alternative approaches to quantify operational efficiency: Stochastic Frontier Analysis (SFA), and Data Envelopment Analysis (DEA). To obtain efficiency measures using these techniques, we examine how efficiently companies utilize available resources (major asset and expense categories in the financial statements) to generate revenue and gross profit. We first employ SFA to estimate technical efficiency for each firm-year in our sample.[5] This technique, first proposed by Aigner, Lovell and Schmidt (1977), has been used extensively in production economics and industrial organization research. SFA 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. It accounts for the possibility that the frontier is subject to stochastic perturbations. A firm's distance from the efficient frontier measures its *relative* inefficiency. Next, we use DEA to measure operational efficiency. This technique, first introduced by Charnes, Cooper and Rhodes (1978), evaluates the relative performance of an

[5] SFA literature uses the label "technical" efficiency to describe how efficiently an output is generated utilizing a vector of inputs, given a technological regime. In this study, we use the terms "technical" and "operational" efficiencies interchangeably.

organizational Decision Making Unit (DMU), and has been used extensively in diverse fields. The DEA technique envelopes observed data to form a piecewise linear frontier that depicts the most technically efficient combination of inputs and outputs, and then uses this frontier to measure the relative efficiency of a DMU. DEA adopts a mathematical programming approach to estimate the Pareto-efficient frontier instead of the parametric statistical approach employed by SFA. Consequently, DEA does not require an *a priori* assumption of a production function.[6]

We first use the SFA approach to estimate a single frontier pooling all industries together, and compare the average efficiency of each firm in the post-IFRS period with its own average efficiency estimate in the pre period. We find strong evidence that SFA-based firm-specific efficiencies improve after the IFRS adoption. We next estimate the frontier separately for three R&D intensive industries and find qualitatively similar evidence of efficiency gains from the pre to post periods. Our SFA-based tests are robust to various sensitivity analyses, including alternative model specifications, and the use of several alternative sets of input variables. Our analyses (both the main tests and the robustness checks) based on the DEA approach yield very similar results. Consistent results from two sophisticated measurement techniques, each with its own set of stylized assumptions, attest to the robustness of our findings. Our analyses, thus, suggest that partial capitalization of R&D, allowable under *IAS 38*, is associated with an improvement in the operational efficiency of publicly traded German firms.

Our inferences, however, are susceptible to other validity threats, and we discuss next how we attempt to mitigate each of these concerns. First, as mentioned earlier, companies that invest heavily in R&D are fundamentally different from the rest of the market, so endogeneity due to self-selection poses a serious challenge to any inquiry involving R&D intensive firms. We examine the shift in the accounting regime in Germany around the IFRS adoption to address this issue. Since mandated IFRS adoption is an exogeneous shock, our examination of performance of German firms before and after this event likely mitigates the concern of self-selection. Second, correlated omitted firm attributes pose another validity

[6] Section 3 discusses the SFA and DEA measurement techniques in details. This section also explains why Ordinary Least Square (OLS) approach is incapable of addressing our research question, and how SFA and DEA techniques are particularly well suited for our inquiry.

threat to our inference. Our research design of comparing the average efficiency of each firm in the post-IFRS period with its own average efficiency in the pre period allays this concern because each firm acts as its own control. Third, we need to provide assurance that our results are *not* attributable to other accounting rule changes associated with IFRS adoption. In order to rule out this alternative explanation, we conduct a *placebo* test using a *control* sample of firms that never report R&D expense during our entire 17-year sample period. Our *control* firms, while still subject to all other accounting changes as a result of IFRS adoption, are unlikely to be materially affected by the R&D rule change because they have little or no R&D expense. Interestingly, we find no 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 improvements in efficiency of German firms.[7] Fourth, it is possible that a significant macroeconomic event, unrelated to but coincident with the mandatory IFRS adoption in 2005, is driving our results. Note that the evidence of no efficiency gains for our *control* firms helps to allay this concern because a large, macro event would impact our control sample as well. Moreover, we perform an additional robustness check (reported in Sec 5.5) to convincingly eliminate the possibility of such "event-time clustering."

Our results are timely and relevant because the Securities and Exchange Commission (SEC) is yet to decide whether the U.S. should commit to IFRS adoption. One of the issues that is being debated actively is the requirement to capitalize development costs under IFRS. Our evidence, based on a natural experiment offered by the German setting and using established methods of quantifying efficiency, has the potential to inform this debate.

2. Background Literature and the German Setting

2.1. The Debate over the Impact of the R&D Reporting Rule on Firm Performance

[7] In supplementary analysis, we find significant efficiency improvements for U.S. software companies after FAS 86, when they shifted from full expensing of R&D expenses to conditional partial capitalization of software development costs. This evidence further suggests that the efficiency improvement is more likely attributable to the change in the R&D reporting rule rather than other rule changes associated with the IFRS adoption.

A large body of work argues that agency issues motivate managers to opportunistically cut R&D expenditures relative to other types of investments (investments that could be capitalized and amortized over several years in the future) even when under-investment in R&D could be detrimental to the firm, in the long run (see Hall, 2002, for an overview of this literature). One argument put forward by the literature is that the market fails to understand the valuation implication of the R&D expensing rule, and as a result, R&D intensive firms are undervalued (e.g., Chan et al., 2001). This could induce opportunistic managers to strategically cut R&D expenditures. Another motivation is that managers are often under intense pressure to meet earnings targets (e.g., Burgstahler and Dichev, 1997; Skinner and Sloan, 2002). This could prompt managers to reduce investments in R&D to meet the earnings benchmarks.

The other side of the agency argument is that managers in R&D intensive firms are better able to mask their strategic under-investment in R&D projects because Information asymmetry 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 investments are made in long-term R&D projects. 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 want to protect the value of their proprietary knowledge and are unwilling to reveal important information about their R&D investments, thereby exacerbating the information asymmetry for R&D projects (Bhattacharya and Ritter, 1983; Anton and Yao, 2002). Higher level of information asymmetry makes external monitoring more costly and less effective, providing further impetus for managers to reduce desirable R&D investments to manage short-term earnings.

Some commentators, on the other hand, point out that very little rigorous empirical evidence exists in support of the claim that the current accounting practice has adverse consequences for firms and investors. Skinner (2008) critiques studies making this claim by arguing that the results documented in these papers simply reflect that R&D intensive firms have very different economic characteristics, and firms choose to operate in research intensive industries. Therefore, it is unclear to what extent the biases due to self-selection and omitted firm attributes are driving the results reported in these studies.

There is also evidence that the market seems to 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. Venture capitalists generally take large equity positions in high-tech start-ups and play an active role in managing their operations and investments to mitigate information asymmetries associated with high-tech research ventures (Gompers, 1995). Indeed, the explosive growth of the venture capital industry to finance high-tech start-ups in Silicon Valley suggests that this approach is popular in addressing the information asymmetry problem associated with high-tech ventures. In sum, although the current R&D reporting rule raises agency concerns, the debate over the longer-term impact of the rule on firm performance is not settled.

2.2. Evidence on Managerial Manipulations of R&D Expenditures

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 R&D intensive industries and find that CEOs spend less on R&D during their final years in office before retirement. Bushee (1998) reports that 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. 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, difficult to infer that the temporary reductions in R&D, documented in select subsets of firms and under certain special circumstances, eventually render firms less efficient 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 R&D disclosure rule and future firm performance; the current accounting regime in the U.S. is in place for almost four decades. Moreover, as mentioned earlier, the fact that R&D intensive companies are fundamentally different from the rest of the market further complicates this investigation. Interestingly, Germany offers a unique natural experiment that could facilitate this inquiry. We next describe the German setting.

2.3. The German Setting

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*).[8] 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 practice of expensing R&D on longer-term firm performance. We track the performance of the *same* German firm 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. The setting is useful because mandated IFRS adoption is an exogenous shock that allays concerns regarding endogeneity. Our research design also allows a firm to act as its own control, thereby mitigating the confounding effects of correlated omitted firm attributes on performance.

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

[8] 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).

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).[9] 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. Consistent with these findings, a sizable proportion of our sample firms also 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-adoption analysis, whereas firms that adopted IFRS only after the EU mandate (hereafter, timely adopters), we use 2005 as the adoption year.[10]

Finally, Germany is a developed industrialized nation that has a large free-market economy, well established democratic and capitalist institutions, and highly liquid capital markets. Similar to the U.S., Germany also largely relies on technical and knowledge-based innovations, supported by large investments in R&D, as its engine for economic growth (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 (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.

[9] 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, 2006). We also observe that a few early adopters of IAS reverted back to German GAAP later, and our results are robust to eliminating these firms from our analysis.

[10] The fact that some firms voluntarily adopted IFRS early again invokes the concern of endogeneity, whereas no such concern exists for firms that were required to adopt IFRS after the EU mandate. This motivates us to examine the two groups separately, and in Sec 5.5, we present the results of separately analyzing the early adopters and the timely adopters.

In summary, we compare operating efficiencies of German public companies in the pre IFRS-adoption period with operating efficiencies of the *same* set of firms after the IFRS adoption. Improvement in operating efficiencies from the pre period to the post period would suggest that the capitalization of development costs under *IAS 38* likely partially mitigates the problem of opportunistic under-investment in R&D, and/or managers are better able to signal to the market their successes in R&D investments in the partial capitalization disclosure regime.[11] In that vein, one could conclude that partial capitalization of R&D mandated by IFRS has overall beneficial effect on firm performance.

3. Methodology and Research Design

3.1. Stochastic Frontier Analysis

Our first measure of operational efficiency is based on the SFA estimation technique. This technique was first proposed by Aigner, Lovell and Schmidt (1977), and it has been used extensively since then in production economics, operations research and industrial organization literatures to estimate various types of technical efficiencies (e.g., Fried, Lovell and Schmidt, 1993; Lovell, 1996; Fare and Grosskopf, 1997; Coelli, Rao and Battese, 1998, among others). This technique, however, has been used relatively sparsely in the accounting literature. 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. Greene and Segal (2004) use SFA and document a contemporaneous association between profitability (ROE and ROA) and efficiency

[11] An alternative view posits that mandating full capitalization of R&D could lead to over-investments in R&D expenditures. Kanodia, Bushman and Dickhaut's (1989) model demonstrates that managers may continue investments in an existing R&D project even when their private information suggests abandonment due to reputational costs associated with discontinuation and impairment. Seybert (2010) reports using an experimental setting that managers responsible for initiating an R&D project are more likely to over-invest when the accounting regime mandates full capitalization. Consequently, if we observe no significant improvement in efficiency of German firms following the IFRS adoption, the inference is unclear. Such a finding suggests the following equally plausible scenarios: (a) the partial capitalization rule does not substantially mitigate the under-investment problem; (b) the efficiency gains from partially mitigating managers' incentive to under-invest in R&D are outweighed by the efficiency decreases from wasteful over-investments; (c) our statistical tests lack power.

in the U.S. life insurance industry. Callen, Morel and Fader (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 find that SFA-based metrics have incremental explanatory power over traditional ratios.

The SFA 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 production frontier using a parametric approach, and allows for stochastic variations of the frontier due to measurement errors and other random events. 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:

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

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

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

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

u_i is a non-negative random variable assumed to account for technical inefficiency in production and is independent of ν_i.[12]

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 in a panel data setting and include a second equation to explain the variations in technical inefficiency itself. Their model is as follows:

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

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

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. The Battese and Coelli (1995) technique jointly estimates Equations (2) and (3)

[12] 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 Appendix A.

using maximum likelihood estimation to find parameter values of β and δ. This technique uses Ordinary Least Square (OLS) estimation as the first step or starting point of the iterative procedure. Subsequent iterations improve on the OLS values, and generate estimates of u_{it} (the distance from the efficient frontier) for each firm-year in our sample. This specification computes technical efficiency of a firm as a ratio relative to a fully efficient firm on the frontier. The value of this efficiency estimate, $\exp(-u_{it})$, lies between 0 (when u_{it} is infinitely large) and 1 (when u_{it} is 0, its lowest possible value). A more detailed account of the SFA methodology is provided in Appendix A.

For estimating efficiency using SFA, we employ two alternative output measures: Sales Revenue (SALE) and Gross Margin (GM). In our primary analysis, the following variables comprise our input vector (x vector in Equation (2)): 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). CGS is excluded from the input vector when the output metric is GM because of the mechanical relationship between the two. Our input variables are similar to the input measures employed in Baik et al. (2010) and Demerjian et al. (2012).[13] The YEAR variable is included to control for any *Hicksian* temporal expansion of the frontier. An indicator variable called ADOPT, and an intercept are the members of the z vector in Equation (3). ADOPT takes on the value of 1 in the IFRS-adoption year and later years, and 0 otherwise. It measures the change in technical efficiency from pre to post periods.

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, 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 a

[13] We also estimate our models with several alternative input vectors and find broadly similar results. Section 5.7 describes this analysis.

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.[14] This research design, in particular, computes change in efficiency on a firm-by-firm basis, and thus, likely controls for all firm-specific attributes that are unaffected by the accounting rule change.

3.2. Data Envelopment Analysis

We use the DEA technique as an alternative approach to measure firm-specific operational efficiency. This technique was first introduced by Charnes, Cooper and Rhodes (1978) to evaluate the relative performance of an organizational Decision Making Unit (DMU). Since then it has been applied extensively to measure relative efficiencies of DMUs in the economics and management literatures (e.g., Banker, Charnes and Cooper, 1984; Banker and Morey, 1986; Banker and Maindiratta, 1988; Callen, 1991; Fare et al., 1994). In the accounting literature, Callen and Falk (1993) have used DEA to measure relative efficiency for cost variance analysis and performance measurement for non-profit organizations. In a recent study, Demerjian, Lev and McVay (2012) use DEA to propose a new measure of managerial ability, based on managers' efficiency in generating revenues. They document relations between their DEA-based efficiency metric, and current and past returns and several common managerial characteristics.

The DEA technique envelopes observed data points to form a piecewise linear frontier that depicts the most technically efficient combination of inputs and outputs, and then uses this frontier to measure the relative efficiency of a DMU compared to the "best-practice" DMU on the frontier. However, DEA adopts a mathematical programming approach to determine the Pareto-efficient frontier instead of the parametric statistical approach employed in SFA. Since the DEA approach solves a

[14] 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 from the pre to the post period (i.e., the average cross-sectional *efficiency* has increased in the post period). In contrast, the firm-specific estimate obtained from the model quantifies *efficiency*. Thus, when we calculate a firm-specific change 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.

mathematical program, no *a priori* assumption of a production function is needed. Further, unlike SFA, the DEA approach does not require any stylized assumptions about the statistical distributions of the inefficiencies. These characteristics make the DEA approach more easily generalizable than SFA. DEA, on the other hand, suffers from the limitation that it, unlike SFA, does not explicitly account for the possibility that the efficient frontier itself could be subject to stochastic perturbations. Further, since DEA constructs a deterministic frontier, it is more sensitive to outliers, and diagnostic tools are limited (Wilson, 1995). Therefore, SFA and DEA methodologies seem to have complementary characteristics, and consistent results using both approaches are likely to be quite robust.

To measure changes in relative efficiency before and after IFRS adoption, we employ the *Malmquist Index* following Färe et al. (1994), Grifell-Tatje and Lovell (1995), Lovell (2003) and Banker et al. (2005). For our analysis, each firm is considered a DMU. Change in efficiency based on DEA is computed from the pre-IFRS adoption period to the post adoption period, on a firm-by-firm basis, again subjecting each firm as its own control. We employ the same input-output combination that is used in SFA to operationalize DEA, except that the YEAR variable is no longer included as an input. Since the construction of the *Malmquist Index* requires a balanced panel for two periods, we obtain two data points (one for the pre-IFRS adoption period and one for the post period) for each DMU in our sample by calculating the mean values of its output and input measures in each period. Next, we solve the DEA problem to obtain an efficiency score for each firm-period, and calculate a *Malmquist Index* for each firm to capture the firm-specific change in relative efficiency from pre to post periods. If a firm's *Malmquist Index* is greater than (less than) 1, the firm has become more (less) efficient in the post adoption period. We test whether the geometric mean (median) of firm-level *Malmquist Index* series is greater than 1 using a t-test (signed-rank test). A more detailed account of the DEA methodology and the *Malmquist Index* is provided in Appendix B.

3.3. Advantages of SFA and DEA Approaches over Ordinary Least Square (OLS)

In this section, we explain why the OLS estimation technique seems incapable of addressing our research question, and why the SFA and DEA methodologies are particularly well suited for our inquiry. First, note that the subject of interest is *not* the actual R&D expenditures, but R&D outlays opportunistically withheld by myopic managers leading to sub-optimal resource allocation decisions. Thus, focusing on the coefficient of *reported* R&D expenses from an OLS regression framework would be misleading. In contrast, if opportunistic under-investments in R&D lead to inefficiencies in productions and operations, SFA and DEA techniques are designed specifically to capture such effects. Second, managers do not tweak with one investment in isolation, rather they likely adjust several input factors simultaneously, often compensating a drop in one factor by increasing the level of another. Thus, in certain circumstances, managers may have economically viable reasons for substituting R&D in favor of investments in other assets. Consequently, the marginal effect of *reported* R&D expense from an OLS regression is not meaningful because an increase in the *reported* R&D coefficient alone from pre to post periods does not necessarily signal inferior performance in the pre period. Third, a measurement issue further complicates the interpretation of a change in the *reported* R&D coefficient from pre to post periods. IFRS does not mandate specific disclosure of capitalized development expenditure, and consequently, it is capitalized and subsequently amortized under various asset and expense categories in the post-adoption period. Thus, the *reported* R&D expense in the pre-period is not directly comparable with that in the post-period because they are measured differently, and as a result, it is impossible to interpret a change in the *reported* R&D coefficient from pre to post periods from an OLS regression. This measurement problem is less of a concern for operationalizing SFA and DEA because these techniques measure how efficiently an entire vector of inputs maps into an output. As mentioned in Footnote 12, we employ several alternative sets of input vectors in our main and sensitivity tests that contain the major asset and expense categories. Consequently, it is likely that in most instances, our input vectors capture capitalized and subsequently amortized development costs in the post-adoption period. Fourth, as Footnote 10 suggests, the partial capitalization rule could lead to wasteful over-investments in R&D.

Thus, an increase in the level of R&D expenditure from pre to post periods (i.e., an increase in the R&D coefficient from pre to post periods from an OLS regression), in and of itself, cannot be interpreted as a desirable outcome. SFA and DEA, on the other hand, penalize both under- and over-investments in R&D as both likely compromise the long-run efficiency of the firm. Finally, the SFA technique *does* employ OLS estimation, but only to generate parameter estimates for the first step of the iterative procedure. Subsequent iterations based on maximum likelihood improve upon the OLS estimates to arrive at the most technically efficient combination of inputs and output.

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 database for the years 1995 to 2011.[15] 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. We identify 1,226 firms (13,055 firm-years) for which financial statement data are available in Worldscope during our sample period. Next we eliminate firm-year observations with missing data and negative values for our primary output and input variables – SALE, CGS, SG&A, lag_PPE, lag_RD and lag2_RD. This data screen results in a loss of 6,597 firm-year observations. Due to this data screen, 300 firms are dropped from our sample because all firm-year observations of these firms are lost. Of the remaining 926 firms, the data screen results in loss of some (but not all) firm-year observations. Further, in order to calculate the change in technical efficiency from pre to post periods using each firm as its own control, we require that each firm in our sample has at least one observation in both the pre and the post-adoption periods. This restriction eliminates 546 firms (2,540 firm-years). Finally, we delete 136 firms (1,257 firm-years) from our primary analysis because these companies never reported R&D expense during our entire 17-year sample period. We feel that these firms are unlikely to be materially affected by the change in the

[15] We compare coverage (using the SEDOL code) of German publicly traded companies in these four databases: Thomson Reuters Worldscope, Compustat Global, Bureau van Dijk AMADEUS and Bureau van Dijk OSIRIS. We find that Worldscope has the most comprehensive coverage.

accounting treatment of R&D. We later use the firms thus deleted as a *control* sample for a placebo test reported in Section 5.3. Our final sample consists of 244 firms and 2,661 firm-year observations from 1995 to 2011.[16]

5. Empirical Results

5.1. Descriptive Statistics

Table 2 provides descriptive statistics for our variables of interests. The table shows that the medians are generally much lower than the means for all the input and output variables in our full sample as well as in the sub-samples of early adopters and timely adopters. Our use of log-transformed variables in all model estimations helps to mitigate the effect of skewness. Panels B and C provide descriptive statistics for the early adopters and timely adopters. We find that early adopters have smaller mean values but larger median values compared to timely adopters. In untabulated analysis, we compare the R&D intensity of our sample firms with that of U.S. public companies. R&D intensity of a firm is defined as R&D expense over sales. After eliminating missing and zero R&D values, the mean (median) R&D intensity of our sample of German public companies is 6.7% (3.8%). The mean (median) R&D intensity of active Compustat companies over the same period (1995-2011) after eliminating missing and zero R&D is 12.4% (6.8%). Thus, overall, German companies have lower R&D intensity than U.S. companies, although, R&D investments of German firms are clearly large and non-trivial.

We report the efficiency estimates based on SFA by year in Panel D of table 2.[17] In order to assess the time-series stability of our efficiency estimates based on SFA, we compute (not tabulated) the serial correlation of the efficiency estimates in adjacent years (i.e., years *t-1* and *t*) for our sample period,

[16] When the output measure is GM, we further delete observations with negative GM because we use log transformed input and output measures, resulting in slightly smaller sample sizes (243 firms and 2,644 firm-year observations).

[17] As mentioned earlier, for our DEA analysis, we rely on the *Malmquist Index* to capture relative efficiency change on a firm-by-firm basis. Since the construction of the *Malmquist Index* requires a balanced panel for two periods, we obtain two data points (one for the pre-IFRS adoption period and one for the post period) for each DMU in our sample by calculating the mean values of its output and input measures in each period. As a result, our DEA approach does not generate efficiency measures by year.

excluding the adoption years. The correlation is very high (Spearman correlation is 0.81 while the Pearson correlation is 0.73) indicating that the efficiency estimates are quite stable over time.

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 only report industries with more than 20 firms. Business Services (SIC 73) has the most number of firms at 50. The next two industries are: Industrial Machinery and Equipment (SIC 35) with 31 firms, and Electronic and Other Electric Equipment (SIC 36) with 27 firms. This clearly limits our ability to run our analysis by industry. However, we replicate our main analysis separately for the three most populous industries and report these results in addition to our pooled sample results.

5.2. Main Analysis

In our main test, we compare the operational efficiencies of all the companies in our final sample before and after the IFRS adoption. Panel A of Table 3 reports results where operational efficiencies are based on SFA, while Panel B reports results where efficiencies are based on DEA.[18] As described in Section 3.1, our primary test of change in efficiency based on SFA involves estimating the Battese and Coelli (1995) specification, i.e., jointly estimating Equations (2) and (3) using maximum likelihood. The z vector in 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. A negative and significant coefficient δ on the ADOPT variable indicates that the level of inefficiency is lower (efficiency is higher) in the post-adoption period relative to the pre period, on average, across the pooled sample. Panel A of the table shows that δ is negative and significant for both the outputs (SALE and GM) indicating that overall technical efficiency has improved significantly in the post-adoption period across the entire pooled sample. In addition, we use the Battese and Coelli (1995) specification to generate an efficiency score for each firm in each year, and compute the firm-specific change in efficiency as the average post-period efficiency estimate of a firm minus its own average pre-period efficiency. We report the mean and median

[18] 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.

values of this firm-specific change series. Since these are efficiency scores, a positive and significant mean or median would indicate efficiency gain in the post-IFRS adoption period. Panel A of Table 3 shows that the mean (median) value of the firm-specific change in efficiency when output is SALE is 0.021 (0.018), and it is highly significant suggesting that technical efficiency increased following the IFRS adoption. The results are similar when GM is used as the output.

Panel B of Table 3 reports efficiency measures based on DEA. As mentioned in Sec 3.2, we compute *Malmquist Index* of relative change in efficiency from the pre-adoption period to the post period, on a firm-by-firm basis, and report the geometric mean and median values of this firm-specific change series. We find that for both output measures (SALE and GM), the geometric mean and median values of the firm-specific change in *Malmquist Index* are all significantly greater than one. For example, the geometric mean (median) when the output is GM is 1.554 (1.567). 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 companies.

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 not entirely clear if the improvement in efficiency is attributable to the change in the R&D reporting rule, or the efficiency gain comes from 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 any individual rule change. In order to tie our results directly to the 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 2011 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 with no reported R&D expense 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. In other words, the firms with no reported R&D expenses serve as our *control* sample in more directly establishing the link between the change in the R&D disclosure rule and the efficiency gains of R&D intensive German firms following the IFRS adoption.

The "no-R&D" sample consists of 136 firms (1,257 firm-year observations) that have never reported R&D expenses during our entire sample period of 17 years (1995 to 2011) and have at least one observation in the pre- and post-adoption periods. 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, and YEAR is excluded in our DEA measurements. We report the results from this analysis in Table 4. Panel A reports results based on the SFA approach, and we find no evidence of efficiency gain in our pooled sample analysis as well as analysis based on efficiency changes on a firm-by-firm basis. 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. Panel B reports results based on the DEA method, and again these results are completely consistent with the evidence obtained from SFA-based efficiency estimates. The geometric mean and median values of the change in *Malmquist Index* are never greater than one.

In sum, Table 4 reports that the group of German firms with no reported R&D expenses experiences *no* improvement in efficiency following the IFRS adoption. If the efficiency gain comes from other rule changes associated with the IFRS adoption, or from the overall beneficial effects of global convergence, this *control* group would have likely experienced efficiency gains as well following the IFRS adoption. Therefore, collectively, the analyses reported in Tables 3 and 4 suggest 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.[19]

[19] In un-tabulated analysis, we further find: (1) the reported R&D expenses increase on average after IFRS adoption. The magnitude of firm-specific changes in efficiency (SFA based) is positively associated with the magnitude of

5.4. Industry-Specific Analysis

Our pooled sample analysis discussed above estimates a single frontier using all firms in our sample. This is a restrictive assumption since different industries likely have different input-output relationships, and pooling all industries together obscures the distinct differences across industries. We resort to estimating a single frontier because we have a fairly small number of German firms (244 companies) with all relevant data available in Worldscope for our sample period from 1995 to 2011. It is, however, important to replicate our main tests separately for the main industries. Consequently, we run tests separately for the three most populous industries in our sample (even for these industries, the number of firms in each industry varies from 27 to 50). These results are reported in Table 5.[20]

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 (50 firms). Panel A1 reports results based on SFA efficiency measures, and we find that the coefficient δ on the indicator variable ADOPT is negative and significant for both of our output measures suggesting that inefficiency is lower in the post-adoption period across the pooled sample. We also find similar results when we compare firm-specific change in efficiency. The mean and median values of the firm-specific change series are significantly positive for both the output measures. Panel A2 reports results when we use DEA to quantify efficiency on a firm-by-firm basis. The DEA results are consistent with our findings based on SFA; the geometric mean and median values of the change in *Malmquist Index* are always significantly greater than one. 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.

Panel B of Table 5 reports results of constructing the frontier using firms only in the Industrial Machinery and Equipment industry (SIC 35). Panel B1 reports results using SFA-based efficiency

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firm-specific changes in R&D expenses; (2) when we expand the vector of z in Battese and Coelli (1995) joint estimation to include the interaction of ADOPT with the firm's mean R&D intensity in the pre-period, the coefficient on the interaction term is negative and significant (p-value<0.0001), suggesting firms with higher R&D intensity in the pre-period experience more efficiency improvement after IFRS adoption.

[20] To improve the power of our tests, all of our empirical tests, except for the industry-specific analysis reported in Table 5, are based on the full sample.

estimates, and the coefficient δ is again significantly negative for both SALE and GM. Firm-specific change in efficiency estimates are also positive and significant for both of our output measures. Panel B2 reports results using DEA-based efficiency measures, and the geometric mean and median of the change in *Malmquist Index* are significantly greater than one for both the outputs. Hence, we find evidence that the operational efficiency has increased in the post-adoption period for the Industrial Machinery and Equipment industry.

Finally, Panel C reports results for the Electronic and Other Electric Equipment Industry (SIC 36), and the results are consistent with our findings so far. When we use SFA to estimate efficiency (Panel C1), except for one instance, we find evidence of significant efficiency gains in our pooled cross-sectional tests as well as firm-specific change tests. Panel C2 reports results based on DEA, and we find that both the mean and median of the change in *Malmquist Index* are significantly greater than one for our two outputs. In summary, we find that efficiency has improved in all three industries after the IFRS adoption. Thus, the results from estimating the frontier separately for the three most populous industries in our sample are highly consistent with evidence based on constructing a single frontier using all firms.

5.5. Analyses 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. It is, however, important to note that our analysis using the *control* sample alleviates such concern. If a macro event, unrelated but coincident with the IFRS adoption in 2005, affects overall performance of German firms, one would likely observe efficiency gains for firms in our *control* sample as well. We, however, find no evidence of efficiency gains for our *control* firms. Interestingly, the German setting offers another opportunity to reliably eliminate the concern of such "event-time clustering." 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, approximately 52% of our sample firms voluntarily adopted

IFRS prior to 2005, starting as early as 1996. Consequently, we examine separately firms that adopted IFRS earlier than 2005 (early adopters) and those that adopted by mandate in 2005 (timely adopters). This analysis has two important advantages. First, if we find evidence of efficiency gains for the group of firms that adopted earlier than 2005, the concern of a macro event around 2005 driving our results could be reliably mitigated. Second, one could argue that our full-sample results do not fully allay the concern of endogeneity because firms self-select to adopt early, and early adopters comprise a sizable fraction of our sample. However, if we observe efficiency improvements in firms that adopted IFRS only after the EU mandate (an exogeneous event), the concern of endogeneity could be further alleviated. Note that we do not re-construct frontiers separately for the early and timely adopters, rather we rely on firm-specific efficiencies generated from constructing the frontier using the full sample.[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 using the SFA and DEA approaches.

The results of this analysis are reported in Table 6. Panel A reports results for the timely adopter group. Our SFA-based estimation (Panel A1) shows that timely adopters experience increases in technical efficiency on adoption of IFRS that are significant for both of our output variables. Our DEA-based analysis of timely adopters (Panel A2) yields very similar results. Finally, Panels B1 and B2 display results for early adopters where efficiencies are measured using SFA and DEA, respectively. We observe that early adopters also experience increases in technical efficiency that are not just statistically significant but also very similar in magnitude to those of timely adopters. In summary, separately analyzing the early adopters and timely adopters provides further comfort that our results are not driven by an unrelated macro event around 2005, or endogeneity due to self-selection.

5.6. Pseudo-Event Period Analysis

[21] Since these firms co-exist at the same point in calendar time, we feel that it is not appropriate to re-construct separate frontiers for early adopters and timely adopters because separate construction would arbitrarily alter the composition of the "efficient frontier" and the "relative technical efficiency" measures.

In this section, we undertake analysis to ensure that our results are not attributable to temporal trends in efficiency improvements, and mechanical relations inadvertently induced by model assumptions. Productivity exhibits a strong temporal trend as firms, on average, become more productive over time and the efficient frontier expands as a result. However, liberal temporal trends in productivity gains that affect all firms equally are unlikely to influence our results because the SFA and DEA techniques compute technical efficiency of a firm as a *ratio* relative to a fully efficient firm on the frontier. Further, our SFA estimation includes the YEAR variable in the input vector to account for the *Hicksian* expansion of the frontier. Our measurement of technical efficiency, however, could be sensitive to temporal trends of efficiency changes that impact "best performing" firms on the frontier differently from relatively less efficient firms. Furthermore, both SFA and DEA have their own sets of stylized assumptions, and it is unclear whether or not these choices induce mechanical biases in the sense that our computation of technical efficiencies in later years are always greater than those in earlier years. In order to ensure that our results are not attributable to such trends and biases, we undertake a "pseudo-event period" analysis. The idea is to designate a year as a pseudo-adoption year such that there is no known accounting rule change around that year. If our results are simply attributable to temporal trends of efficiency changes that affect firms differentially, and/or mechanical relations that may have been introduced by model assumptions, we would observe that efficiency improves from the pre-pseudo-event period to the post-pseudo-event period even though no significant event has taken place.

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 1998 to 2004 to ensure that the entire sample period falls in the pre-IFRS accounting regime. We then designate the years 1998, 1999 and 2000 as the pseudo pre-adoption period, while the years 2001 through 2004 as the pseudo-post-adoption period.[22] Note that in this design, 2001 has been artificially designated as the adoption year although no

[22] We use 3 years (1998 through 2000) in pre-pseudo-adoption period and 4 years (2001 through 2004) in the post period in order to ensure that our designation of pseudo-event period for timely adopters is consistent with those for early adopters. Note that the designation of pseudo-event period for early adopters is restricted by the facts that the start year cannot be earlier than 2005, and the last year in our sample is 2011.

accounting rule change occurred in that year. 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 through 2011. Note that early adopters are those who voluntarily adopted prior to the mandatory adoption year of 2005. We next assign the years 2005, 2006 and 2007 as the pseudo-pre-adoption period for early adopters, while the years 2008 through 2011 as the pseudo-post-adoption period. 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. Panel A reports results where efficiency is measured using SFA, and we observe that the sign of δ is positive rather than negative. Consistent with this evidence, firm-specific change measures are all significantly negative. These results suggest that technical efficiency has declined in the pseudo-post-adoption period compared to the pre-period. Results using DEA-based efficiency measures (Panel B) are similar. We find no significant change in efficiency from pre to post periods when the output is SALE, while a decline in efficiency when the output is GM. Taken together, the results reported in Table 7 suggest that our evidence of improvement in efficiency of German firms in the post-IFRS accounting period is *not* driven by temporal trends or mechanical biases that result in higher efficiency estimates in later years relative to earlier years even in the absence of an accounting regime change.

5.7. Additional Sensitivity Tests

We run several additional sensitivity tests using efficiency measures obtained from both SFA and DEA approaches to ensure the robustness of our findings. Since SFA- and DEA-based efficiency measures yield qualitatively similar results, in the interest of brevity, we only report results using SFA-based efficiency estimates in Table 8. 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 major macro shocks such as the credit crunch, housing and stock market crashes, severe corporate belt tightening etc. It is not clear how these shocks would affect our model assumptions and measurements, 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 our inferences are unchanged.

Next, we consider the fact that the nature of R&D investment is such that its effects take time to flow into operational efficiencies. We already try to model this attribute by including up to two years of R&D lags in our input vector. Further, the length of our post-adoption periods is typically 7 years for timely adopters, and even longer for early adopters, likely allowing sufficient time for the benefits of R&D investments to materialize. In addition, we introduce a third lag of R&D as an additional input variable, and untabulated analysis shows that the main tenor of our results is unchanged. In yet another variation, we re-estimate our models by starting the post adoption period one year after the adoption year. This allows, in many cases, one more year for the benefits from better R&D investment decisions during the partial capitalization accounting regime to accrue. Again, untabulated results show that this variation does not alter our inferences.

Third, 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 results using this specification and we find that they are completely consistent with our earlier findings.

Finally, we expand our input vector to include Goodwill and Other Intangible Assets except Goodwill as additional input variables. There is further sample attrition when we introduce these two additional 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 summary, the various sensitivity tests reported in this section further attest to the robustness and consistency of our results. Hence, we conclude that the partial

[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.

capitalization of R&D due to the adoption of IFRS by German firms results in improved technical efficiency for these firms.

5.8. Supplementary Analysis using U.S. Software Companies Before and After FAS 86

To further ascertain that the documented improvement in efficiency is attributable to the change in the R&D reporting rule, but not other rule changes associated with the IFRS adoption, we exploit an alternative natural experiment setting in the U.S. software industry. Effective 1986, FASB's *statement No. 86* (FAS 86) mandates that once technological feasibility is established, U.S. software companies should capitalize software development costs as assets. Therefore, we are able to track the performance of the same U.S. software company under two R&D reporting regimes – one prior to mandatory FAS 86 adoption when all R&D costs have to be expensed, and one after the FAS 86 adoption when partial capitalization has been allowed. This setting offers a unique opportunity to disentangle the effect of R&D reporting rule from the confounding effects of other rule changes associated with the IFRS adoption, because it mandates virtually the same changes in the R&D reporting rule from full expensing to conditional partial capitalization as IFRS, while free from other IFRS rule changes.

We impose the same sample selection criteria of Table 1 on U.S. firms in the software industry (SIC codes 7371-7374). A final sample of 97 firms and 671 firm-year observations from 1981 to 1991 (excluding the adoption year 1986) is used to estimate the efficiency frontier. Our primary test of change in efficiency based on SFA involves the joint estimation of Equation (2) and (3) in the Battese and Coelli (1995) specification, where the z vector in Equation (3) contains an intercept term and the indicator variable, FAR86ADOPT, that takes the value of 1 for each of the 5 years after the adoption of FAS 86 (1987-1991), and 0 for each of the 5 years before the adoption of FAS 86 (1981-1985). A negative and significant coefficient δ on FAS86ADOPT indicates that the level of inefficiency is lower (efficiency is higher) on average in the post-FAS86 period relative to the pre-FAS86 period.

Table 9 reports that δ is negative and significant for both the outputs (SALE and GM) indicating that overall technical efficiency has improved significantly in the post-FAS86 period for firms in the U.S. software industry. We also find similar results when we compare firm-specific change in efficiency. The mean and median values of the firm-specific efficiency change series are significantly positive for both output measures.[25] Collectively, the results reported in Table 3, Table 4 and Table 9 suggest that the documented efficiency improvement is more likely attributable to the change in the R&D reporting rule than other rule changes associated with IFRS adoption.

6. Conclusions

U.S. GAAP (*SFAS* 2) currently mandates expensing R&D outlays as incurred. In this study, we investigate whether the current accounting rule of expensing R&D leads to firm-specific operational inefficiency. The current rule has been in place since 1974 making it difficult to address its desirability. Moreover, R&D intensive companies are fundamentally different from the rest of the market. As a result, any inquiry involving R&D intensive companies is susceptible to the concern of endogeneity due to self-selection. Germany offers a unique natural setting that aids this investigation. German GAAP used to require, prior to IFRS adoption, that R&D investments be expensed as incurred. Germany adopted IFRS from 2005 and *IAS 38* requires that while research costs should be expensed, development expenditures should be capitalized once technical and commercial feasibilities have been established. If the accounting rule of expensing R&D incentivizes myopic managers to opportunistically cut R&D, this incentive would be lower, and consequently under-investment in R&D would also be lower for German firms 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 and timely manner without having to reveal important proprietary information. This could result in less information asymmetry 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. Since the mandated IFRS adoption is an exogenous event, the concern of endogeneity due to self-selection could also be largely mitigated.

[25] Since SFA- and DEA-based efficiency measures yield qualitatively similar results, in the interest of brevity, we only report results using SFA-based efficiency estimates in Table 9.

We analyze a sample of German public companies over the years 1995 to 2011, and use the SFA and DEA techniques to quantify firm-specific technical efficiency. We first construct 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 construct frontiers separately for the three most populous industries in our sample and find similar results. In order to ensure that our results are *not* attributable to other accounting changes associated with the IFRS adoption, rather than the R&D rule change, *per se*, we run our main tests on a *control* group of German companies that have never reported R&D expense during our entire sample period. We, however, find no evidence of efficiency gains in the post-IFRS period for our *control* firms suggesting that the change in the R&D reporting rule is the likely driver of the efficiency gains in the post-IFRS disclosure regime. Further, to rule out the possibility that a macro event occurring around 2005 but unrelated to the IFRS adoption is driving our results, we conduct separate analyses for firms that adopted IFRS in 2005 and firms that voluntarily adopted IFRS prior to 2005. The two sub-samples yield qualitatively similar results providing further comfort that our inferences are unlikely to be affected by a major unrelated event around 2005. Finally, our results are robust to several additional sensitivity tests, including alternative model specifications and several alternative sets of input and output measures for estimating technical efficiency.

We conclude that our evidence indicates that the partial capitalization of R&D allowable under IFRS is the likely catalyst for the observed improvement in efficiency of German publicly traded companies following the IFRS adoption. Our evidence sheds light on the important and long-standing debate of whether or not the current R&D reporting rule in the U.S. has undesirable consequences for firms and investors. We, thus, believe that our evidence is timely and relevant for standard setters and regulators in the U.S. and abroad.

Appendix A: 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:

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

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.[26] 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:

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

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

[26] 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.

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 setting 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):

$$\ln q_{it} = \ln x_{it}\beta + (v_{it} - u_{it}) \qquad i = 1, 2, \ldots I; \; t = 1, 2, \ldots T \qquad \text{(A4)},$$

$$u_{it} = z_{it}\delta + w_{it} \qquad \text{(A5)}.$$

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.

Appendix B: Data Envelopment Analysis

The Data Envelopment Analysis (DEA) technique envelopes observed data points to form a piecewise linear frontier that depicts the most technically efficient combination of inputs and outputs, and then uses this frontier to measure the relative efficiency of a Decision Making Unit (DMU) compared to the "best-practice" DMU on the frontier. DEA employs a mathematical programming approach to estimate the Pareto-efficient frontier. The efficiency score of each DMU is computed as the ratio of the sum of weighted outputs to the sum of weighted inputs, adjusted to a number between 0 and 1. Thus, efficient DMUs located on the frontier are assigned an efficiency score of 1, while relatively inefficient DMUs inside the frontier are assigned efficiency scores of less than 1.

The output-oriented DEA model that assumes variable returns to scale can be expressed as follows (Coelli et al., 2005):

$$\left[D_0^t(x_0^t, y_0^t)\right]^{-1} = \max_{\phi,\lambda} \phi \qquad \text{(B1)},$$

subject to: (i) $\phi y_0^t \le \sum_{i=1}^{n} \lambda_i^t y_i^t$,

(ii) $x_0^t \ge \sum_{i=1}^{n} \lambda_i^t x_i^t$,

(iii) $\lambda_i^t \ge 0$,

(iv) $\sum_{i=1}^{n} \lambda_i^t = 1$.

This specification involves *n* DMUs. The DMU selected for evaluation is called the *test unit*, and denoted by subscript 0. y_i^t is the vector of outputs for the i-th DMU; x_i^t is the vector of inputs for the i-th DMU; ϕ is a scalar, or expansion factor on the test unit's outputs; λ is an *n*-dimensional vector of non-negative "envelopment weights." The function, $D_0^t(x_0^t, y_0^t)$, measures the relative efficiency of the test unit's input-output combination, (x_0^t, y_0^t), based on the technology in period t. It is normalized to an efficiency score that lies between 0 and 1. The closer the test unit is to the frontier, the greater the efficiency score. Thus, fully efficient DMUs located on the frontier are assigned an efficiency score of 1, while relatively inefficient DMUs inside the frontier are assigned efficiency scores of less than 1.

To measure changes in relative efficiency before and after IFRS adoption, we use the *Malmquist Index* following Färe et al. (1994), Grifell-Tatje and Lovell (1995), Lovell (2003) and Banker et al. (2005). We decompose the index into two components: one to measure the change in relative efficiency, and the other to capture the effect of technology changes. Consider two data points for test DMU 0: (x_0^t, y_0^t) in the base period t, and (x_0^{t+1}, y_0^{t+1}) in the subsequent period *t+1*, the *Malmquist Index* is defined as follows: $M_0^t(x_0^t, y_0^t, x_0^{t+1}, y_0^{t+1}) = [\frac{D_0^t(x_0^{t+1}, y_0^{t+1})}{D_0^t(x_0^t, y_0^t)} \times \frac{D_0^{t+1}(x_0^{t+1}, y_0^{t+1})}{D_0^{t+1}(x_0^t, y_0^t)}]^{\frac{1}{2}}$

$$= \frac{D_0^{t+1}(x_0^{t+1}, y_0^{t+1})}{D_0^t(x_0^t, y_0^t)} \times [\frac{D_0^t(x_0^{t+1}, y_0^{t+1})}{D_0^{t+1}(x_0^{t+1}, y_0^{t+1})} \times \frac{D_0^t(x_0^t, y_0^t)}{D_0^{t+1}(x_0^t, y_0^t)}]^{\frac{1}{2}}.$$

We focus on the first component, $\text{MALM\_EFF}_0 = \frac{D_0^{t+1}(x_0^{t+1}, y_0^{t+1})}{D_0^t(x_0^t, y_0^t)}$, that measures the relative efficiency change of the test unit from period *t* to period *t+1*, after isolating out the component of the technical change.[27]

For our analysis, each firm is considered a DMU. Since the construction of the *Malmquist Index* requires a balanced panel for two periods, we obtain two data points for each DMU in our sample by calculating the mean values of its output and input measures for each period. We then solve the DEA problem to obtain firm-specific efficiency scores, and construct MALM_EFF_0 for each DMU in our sample. Färe et al. (1994) show that $\text{MALM\_EFF}_0 > 1$ indicates an improvement of relative efficiency in period *t+1* relative to the base period *t*. Likewise, $\text{MALM\_EFF}_0 < 1$ indicates a deterioration in relative efficiency, and $\text{MALM\_EFF}_0 = 1$ means no change in relative efficiency, from per to post periods.

[27] Our DEA computations, following Banker et al. (2005), allow variable returns to scale. As a result, MALM_EFF_0 captures *pure* relative efficiency change without complications of scale efficiency change. Our results are stronger if we use *Malmquist Index* of technical efficiency change relative to a constant returns to scale technology, or if we use *Malmquist Index* of total factor productivity change.

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FIGURE 1

Technical Inefficiency in a Stochastic Efficient Frontier

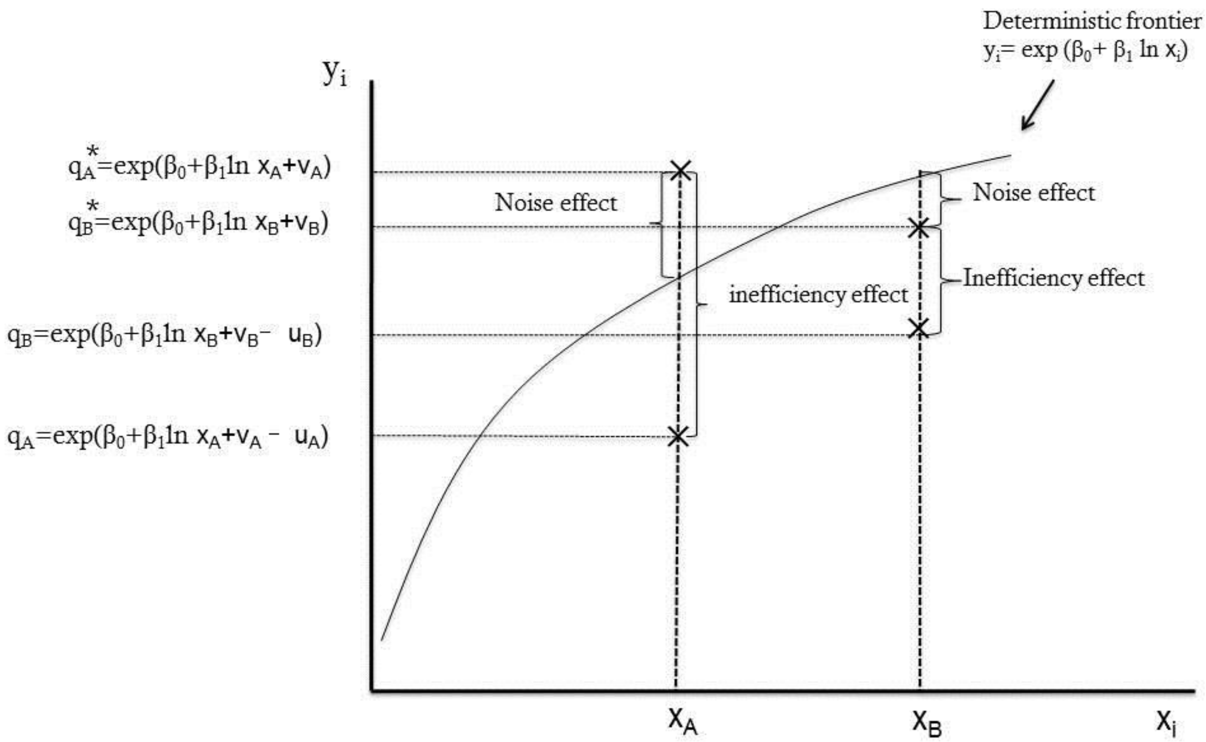
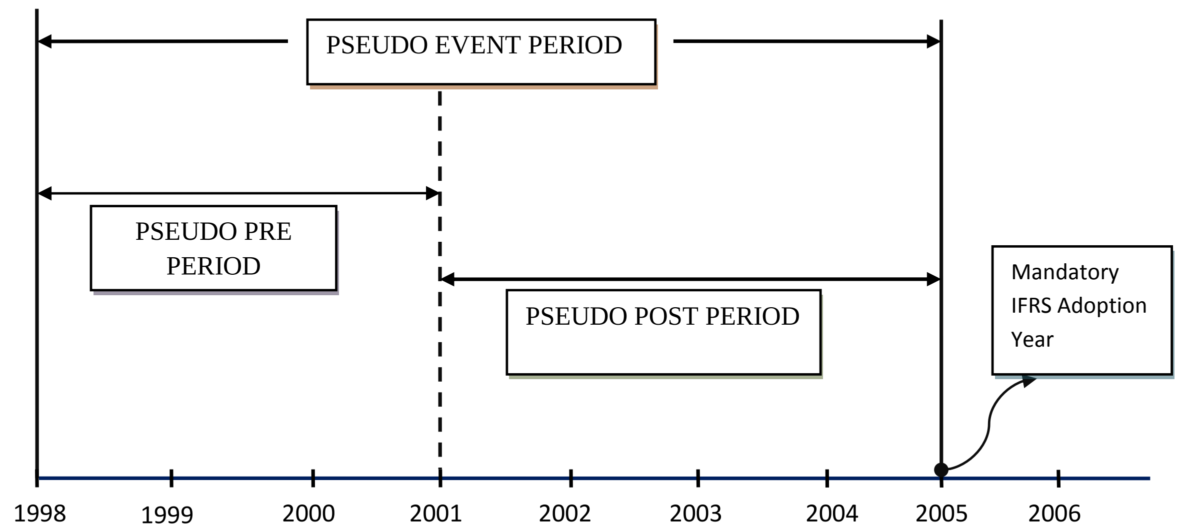


FIGURE 2

Pseudo Event-Periods for Timely and Early Adopters

Panel A: Timely Adopters



Panel B: Voluntary Early Adopters

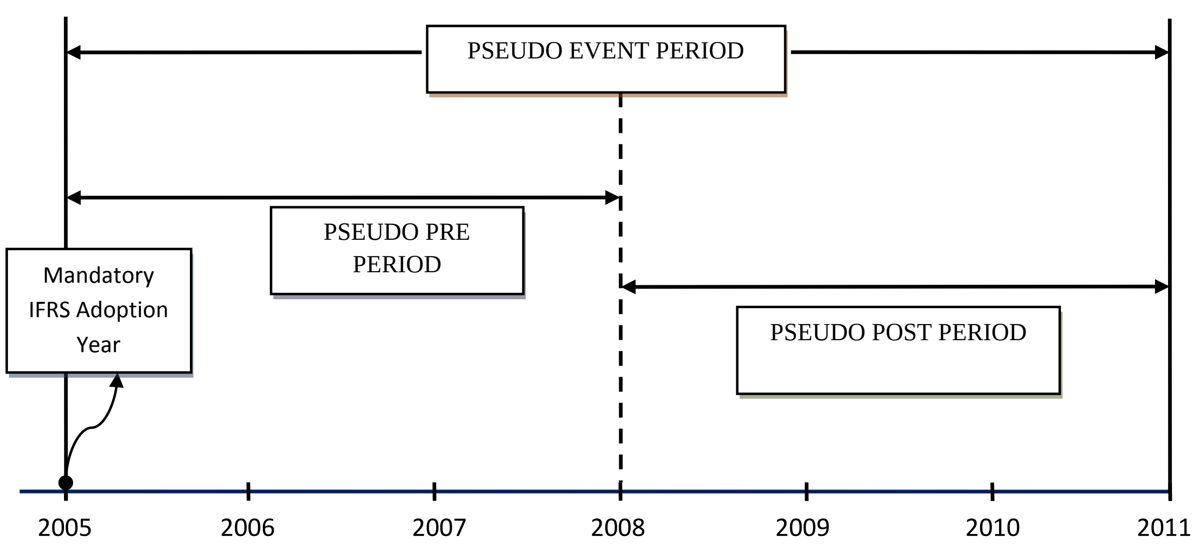


Table 1 **Sample Selection**

* For each of these 300 firms, all firm-year observations are lost due to this data screen, resulting in deletion of these firms from our sample. For each of the remaining 926 firms, the data screen results in loss of some (but not all) firm-year observations.

We employ the sample described in Table 1 for our primary analyses where we pull all industries together for estimating a single frontier to operationalize SFA or DEA.

Sample Selection Procedure	Number of Firms	Firm-Years
Publicly traded German firms with financial statement data available in Worldscope database during the period, 1995-2011	1,226	13,055
Observations with missing data or negative values of the output and input variables*	(300)	(6,597)
Firms that do not have at least 1 observation both before and after the IFRS adoption year.	(546)	(2,540)
Firms that never reported R&D expenditure during our entire sample period from 1995 to 2011.	(136)	(1,257)
Final Sample	244	2,661

Table 2 Descriptive Statistics

***** The reported frequencies are based on the full sample of 2,661 observations. When the output metric is GM, we further delete firm-years with negative GM to facilitate log transformation. This causes the number of observations when the output is GM (reported in parenthesis) to be slightly different for some years.
†39 industries (classified by 2-digit SIC code from 01 to 89) are represented in the sample. In order to avoid clutter, only industries with more than 20firms 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.

All the variables reported in Panels A through C are in millions of Euros. The definitions are given below:

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

CGS: Cost of goods sold as reported in WorldScope.

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

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

Panel A: Full Sample

Variables	Firm-Years	Mean	Median	Standard Deviation
Output Metric				
SALE	2,661	5,282	191	16,338
GM	2,644	1,659	63	5,052
Input Vector				
CGS	2,661	3,634	127	11,753
SGA	2,661	927	42	2,852
Lag_PPE	2,661	1,838	27	7,117
Lag_RD	2,661	151	2.41	607
Lag2_RD	2,661	142	1.79	586

Panel B: Early Adopters

Variables	Firm-Years	Mean	Median	Standard Deviation
Output Metric				
SALE	1,400	3,759	319	9,015
GM	1,394	1,179	89	2,967
Input Vector				
CGS	1,400	2,585	218	6,482
SGA	1,400	668	53	1,650
Lag_PPE	1,400	1,100	32	3,736
Lag_RD	1,400	92	2.58	364
Lag2_RD	1,400	84	1.79	340

Panel C: Timely Adopters

Variables	Firm-Years	Mean	Median	Standard Deviation
Output Metric				
SALE	1,261	6,972	146	21,629
GM	1,250	2,194	51	6,607
Input Vector				
CGS	1,261	4,798	92	15,569
SGA	1,261	1,214	36	3,741
Lag_PPE	1,261	2,657	24	9,495
Lag_RD	1,261	217	2.30	789
Lag2_RD	1,261	207	1.79	767

Panel D: Distribution of SFA-Based Efficiency Measures by Year

		Output: SALE		Output: GM	
Year	Firm-Years*	Mean	Median	Mean	Median
1995	43	0.912	0.913	0.752	0.763
1996	51	0.915	0.912	0.762	0.763
1997	57	0.917	0.914	0.777	0.775
1998	76	0.912	0.914	0.760	0.776
1999	101	0.912	0.915	0.770	0.789
2000	135 (134)	0.908	0.916	0.780	0.801
2001	159 (157)	0.903	0.915	0.745	0.798
2002	203 (200)	0.910	0.915	0.746	0.778
2003	219 (216)	0.914	0.917	0.751	0.779
2004	227 (224)	0.918	0.925	0.775	0.809
2005	234 (232)	0.925	0.930	0.794	0.818
2006	229 (228)	0.927	0.932	0.809	0.826
2007	222	0.928	0.932	0.805	0.836
2008	213	0.929	0.932	0.814	0.835
2009	197 (196)	0.927	0.930	0.799	0.826
2010	192 (191)	0.927	0.933	0.812	0.836
2011	103	0.928	0.933	0.829	0.845

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	31
36: Electronic & Other Electric Equipment	27
38: Instruments and Related Products	22
73: Business Services	50

Table 3 Comparisons of Operational Efficiency Before and After IFRS Adoption for the Full Sample

A sample of 244 (243) firms and 2,661 (2,644) firm-year observations are used to estimate the frontier when the output metric is SALE (GM). 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. YEAR denotes the observation year, and it is included to control for any *Hicksian* temporal expansion of the frontier. All other variables are defined in Table 2. In Panel A, we estimate the operational efficiency for each firm-year using the SFA method. We use the Battese and Coelli (1995) approach 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. In this specification, a *negative* and significant coefficient δ on ADOPT would indicate a significant improvement in efficiency in the post-IFRS adoption period relative to the pre period. We also separately calculate average efficiency for the pre and post periods for each firm in our sample. We then calculate the change in efficiency for each firm as the average post-period efficiency estimate of the firm minus its own average pre-period estimate. We then test the significance of the mean (median) change in efficiency using a t-test (signed-rank test). A *positive* and significant mean or median value would indicate efficiency improvement in the post period. In Panel B, we employ the DEA-based *Malmquist Index* of pure efficiency change ($MALM\_EFF_0$) to measure change in efficiency across the two periods. We use the same input-output combination that is used in SFA, except that the YEAR variable is no longer included as an input. We obtain two data points (one for the pre-IFRS adoption period and one for the post period) for each DMU in our sample by calculating the mean values of its output and input measures in each period. Next, we solve the DEA program to obtain an efficiency score for each firm-period, and calculate a *Malmquist Index* for each firm to capture the firm-specific change in relative efficiency from pre to post periods. If a firm's *Malmquist Index* is greater than (less than) 1, the firm has become more (less) efficient in the post adoption period. We test whether the geometric mean (median) of firm-level *Malmquist Index* series is greater than 1 using a t-test (signed-rank test). Numbers in parentheses are *p-values* from two-tailed tests.

Panel A: Changes in SFA-Based Relative Efficiency

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 *test statistic* (*p-value*)	Signed-rank test of Median *test statistic* (*p-value*)	Magnitude of coefficient δ (*p-value*)
SALE	244	0.021	0.018	7.48 (<0.0001)	11808 (<0.0001)	-1.36 (<0.0001)
GM	243	0.063	0.053	8.41 (<0.0001)	9441 (<0.0001)	-5.49 (<0.0001)

Panel B: Changes in DEA-Based Relative Efficiency

Output Metric	Malmquist index of pure relative efficiency change (Post-IFRS adoption measure relative to pre-IFRS adoption measure)				
	Number of firms	Geometric Mean of firm-specific $MALM\_EFF_0$	Median of firm-specific $MALM\_EFF_0$	t-test of Mean=1 *test statistic* (*p-value*)	Signed-rank test of Median=1 *test statistic* (*p-value*)
SALE	244	1.182	1.152	9.80 (<0.0001)	9235 (<0.0001)
GM	243	1.554	1.567	12.21 (<0.0001)	11027 (<0.0001)

Table 4 Comparisons of Operational Efficiency Before and After IFRS Adoption for the "No-R&D" Sample

The No-R&D sample consists of 136 firms (1,257 firm-year observations) that have *never* reported R&D expenses during our sample period (1995-2011) and have at least 1 observation both before and after the IFRS adoption year. The outputs are SALE and GM, respectively. 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. YEAR denotes the observation year, and it is included to control for any *Hicksian* temporal expansion of the frontier. All other variables are defined in Table 2. In Panel A, we estimate the operational efficiency using the SFA method. We use the Battese and Coelli (1995) approach 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. In this specification, a *negative* and significant coefficient δ on ADOPT would indicate a significant improvement in efficiency in the post-IFRS adoption period relative to the pre period. We also separately calculate average efficiency for each firm in our sample, and compute the change in efficiency for each firm as the average post-period efficiency estimate of the firm minus its own average pre-period estimate. We test the significance of this mean (median) change series using a t-test (signed-rank test), and a *positive* and significant mean or median value would indicate improvement in efficiency. In Panel B, we employ the DEA-based *Malmquist Index* of pure efficiency change ($MALM\_EFF_0$) to measure change in efficiency across the two periods. We use the same input-output combination that is used in SFA, except that the YEAR variable is no longer included as an input. We obtain two data points (one for the pre-IFRS adoption period and one for the post period) for each DMU in our sample by calculating the mean values of its output and input measures in each period. Next, we solve the DEA program to obtain an efficiency score for each firm-period, and calculate a *Malmquist Index* for each firm to capture the firm-specific change in relative efficiency from pre to post periods. If a firm's *Malmquist Index* is greater than (less than) 1, the firm has become more (less) efficient in the post adoption period. We test whether the geometric mean (median) of firm-level *Malmquist Index* series is greater than 1 using a t-test (signed-rank test). Numbers in parentheses are *p-values* from two-tailed tests.

Panel A: Changes in SFA-Based Relative Efficiency

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 *test statistic* (*p-value*)	Signed-rank test of Median *test statistic* (*p-value*)	Magnitude of coefficient δ (*p-value*)
SALE	136	-0.035	-0.033	-3.06 (0.0027)	-1657 (0.0002)	0.63 (0.0025)
GM	136	-0.045	-0.038	-5.83 (<0.0001)	-2946 (<0.0001)	3.70 (0.0054)

Panel B: Changes in DEA-Based Relative Efficiency

Output Metric	Malmquist index of pure relative efficiency change (Post-IFRS adoption measure relative to pre-IFRS adoption measure)				
	Number of firms	Geometric Mean of firm-specific $MALM\_EFF_0$	Median of firm-specific $MALM\_EFF_0$	t-test of Mean=1 *test statistic* (*p-value*)	Signed-rank test of Median=1 *test statistic* (*p-value*)
SALE	136	0.952	0.951	-1.24 (0.2176)	-795 (0.0497)
GM	136	0.840	0.890	-2.97 (0.0035)	-890 (0.0297)

Table 5 Industry-Specific Comparisons of Operational Efficiency Before and After IFRS Adoption

In this Table, we construct efficient frontiers separately for three industries – Panel A reports results for the Business Services industry (SIC 73), Panel B shows results for the Industrial Machinery and Equipment industry (SIC 35), and Panel C displays results for Electronic & Other Electric Equipment industry (SIC 36). Panels A1, B1 and C1 report results based on SFA estimations. The outputs are again SALE and GM. The input vector is the same as in Tables 3. For SFA estimation, we use the Battese and Coelli (1995) approach that jointly estimates Equations (2) and (3) mentioned 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. In this specification, a *negative* and significant coefficient δ on ADOPT would indicate a significant improvement in efficiency in the post-IFRS period relative to the pre period. We also separately calculate average efficiency for each firm in our sample, and compute the change in efficiency for each firm as the average post-period efficiency estimate of the firm minus its own average pre-period estimate. We test the significance of this mean (median) change series using a t-test (signed-rank test), and a *positive* and significant mean or median value would indicate improvement in efficiency. Panels A2, B2 and C2 report results based on efficiency measurements using the DEA-based *Malmquist Index* of pure efficiency change ($MALM\_EFF_0$). We use the same input-output combination that is used for DEA analyses in Table 3. We obtain two data points (one for the pre-IFRS adoption period and one for the post period) for each DMU in our sample by calculating the mean values of its output and input measures in each period. Next, we solve the DEA program to obtain an efficiency score for each firm-period, and calculate a *Malmquist Index* for each firm to capture the firm-specific change in relative efficiency. We test whether the geometric mean (median) of firm-level *Malmquist Index* series is greater than 1 or not using a t-test (signed-rank test), and if it is greater than (less than) 1, the firm has become more (less) efficient in the post adoption period. Numbers in parentheses are *p-values* from two-tailed tests.

Panel A: Business Services (SIC 73)

A1: Changes in SFA-Based Relative Efficiency

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 *test statistic* (*p-value*)	Signed-rank test of Median *test statistic* (*p-value*)	Magnitude of coefficient δ (*p-value*)
SALE	50	0.061	0.048	5.93 (<0.0001)	521 (<0.0001)	-3.47 (0.0005)
GM	50	0.108	0.107	5.29 (<0.0001)	495 (<0.0001)	-6.99 (<0.0001)

A2: Changes in DEA-Based Relative Efficiency

Output Metric	Malmquist index of pure relative efficiency change (Post-IFRS adoption measure relative to pre-IFRS adoption measure)				
	Number of firms	Geometric Mean of firm-specific $MALM\_EFF_0$	Median of firm-specific $MALM\_EFF_0$	t-test of Mean=1 *test statistic* (*p-value*)	Signed-rank test of Median=1 *test statistic* (*p-value*)
SALE	50	1.08	1.05	3.11 (0.0015)	228 (0.0007)
GM	50	1.61	1.71	7.35 (<0.0001)	418 (<0.0001)

Panel B: Industrial Machinery and Equipment (SIC 35)

B1: Changes in SFA-Based Relative Efficiency

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 *test statistic* (*p-value*)	Signed-rank test of Median *test statistic* (*p-value*)	Magnitude of coefficient δ (*p-value*)
SALE	31	0.041	0.030	4.99 (<0.0001)	248 (<0.0001)	-1.10 (0.0122)
GM	30	0.043	0.039	3.56 (0.0013)	157 (0.0005)	-2.41 (0.0519)

B2: Changes in DEA-Based Relative Efficiency

Output Metric	Malmquist index of pure relative efficiency change (Post-IFRS adoption measure relative to pre-IFRS adoption measure)				
	Number of firms	Geometric Mean of firm-specific $MALM\_EFF_0$	Median of firm-specific $MALM\_EFF_0$	t-test of Mean=1 *test statistic* (*p-value*)	Signed-rank test of Median=1 *test statistic* (*p-value*)
SALE	31	1.03	1.02	1.85 (0.035)	70 (0.015)
GM	30	1.22	1.06	3.65 (0.0005)	95 (0.0004)

Panel C: Electronic & Other Electric Equipment (SIC 36)

C1: Changes in SFA-Based Relative Efficiency

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 *test statistic* (*p-value*)	Signed-rank test of Median *test statistic* (*p-value*)	Magnitude of Coefficient δ (*p-value*)
SALE	27	0.037	0.021	2.43 (0.02)	110 (0.0057)	-1.77 (0.1540)
GM	27	0.092	0.072	2.61 (0.0149)	189 (0.0068)	-7.23 (0.0223)

C2: Changes in DEA-Based Relative Efficiency

Output Metric	Malmquist index of pure relative efficiency change (Post-IFRS adoption measure relative to pre-IFRS adoption measure)				
	Number of firms	Geometric Mean of firm-specific $MALM\_EFF_0$	Median of firm-specific $MALM\_EFF_0$	t-test of Mean=1 *test statistic* (*p-value*)	Signed-rank test of Median=1 *test statistic* (*p-value*)
SALE	27	1.05	1.01	1.89 (0.035)	61 (0.015)
GM	27	1.36	1.17	2.76 (0.0055)	88 (0.0023)

Table 6 Separate Analyses for Timely Adopters and Early Adopters

Firms that adopted IFRS by mandate 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-construct SFA or DEA frontier separately for these two sub-groups, rather we rely on firm-specific efficiencies generated from constructing the frontier using the full sample. We next compute firm-specific changes in average efficiencies from the pre to the post periods separately for the early adopters and timely adopters using the SFA and DEA approaches outlined in the earlier tables. Panels A1 and B1 report results based on SFA estimations, while Panels A2 and B2 show results based on efficiency measurements using the DEA-based *Malmquist Index* ($MALM\_EFF_0$). Numbers in parentheses are *p-values* from two-tailed tests.

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

A1: Changes in SFA-Based Relative Efficiency

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 *test statistic* (*p-value*)	Signed-rank test of Median *test statistic* (*p-value*)
SALE	118	0.021	0.019	4.53 (<0.0001)	2771 (<0.0001)
GM	117	0.063	0.055	6.40 (<0.0001)	2340 (<0.0001)

A2: Changes in DEA-Based Relative Efficiency

Output Metric	Malmquist index of pure relative efficiency change (Post-IFRS adoption measure relative to pre-IFRS adoption measure)				
	Number of firms	Geometric Mean of firm-specific $MALM\_EFF_0$	Median of firm-specific $MALM\_EFF_0$	t-test of Mean=1 *test statistic* (*p-value*)	Signed-rank test of Median=1 *test statistic* (*p-value*)
SALE	118	1.19	1.17	6.60 (<0.0001)	2234 (<0.0001)
GM	117	1.56	1.52	8.11 (<0.0001)	2662 (<0.0001)

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

B1: Changes in SFA-Based Relative Efficiency

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 *test statistic* (*p-value*)	Signed-rank test of Median *test statistic* (*p-value*)
SALE	126	0.020	0.015	6.62 (<0.0001)	3160 (<0.0001)
GM	126	0.062	0.051	5.60 (<0.0001)	2401 (<0.0001)

B2: Changes in DEA-Based Relative Efficiency

Output Metric	Malmquist index of pure relative efficiency change (Post-IFRS adoption measure relative to pre-IFRS adoption measure)				
	Number of firms	Geometric Mean of firm-specific $MALM\_EFF_0$	Median of firm-specific $MALM\_EFF_0$	t-test of Mean=1 *test statistic* (*p-value*)	Signed-rank test of Median=1 *test statistic* (*p-value*)
SALE	126	1.18	1.12	7.27 (<0.0001)	2462 (<0.0001)
GM	126	1.55	1.58	9.16 (<0.0001)	2867 (<0.0001)

Table 7 Pseudo Time Period Analysis

This table reports analyses 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 period or the post-pseudo adoption period. We designate pseudo-event years as follows. For timely adopters, we conduct the pseudo-event period analysis over the years 1998-2004 to ensure that the entire sample period falls in the pre-IFRS accounting regime. We then designate the years 1998 through 2000 as the pseudo-pre-adoption period, while the years 2001 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 2005-2011. We next assign the years 2005 through 2007 as the pseudo-pre-adoption period for early adopters, while the years 2008 through 2011as the pseudo-post-adoption period for early adopters. We then pool early and late adopters together and run tests analogous to those reported in Table 3. Estimation procedures and input and output measures are defined in Table 3. Numbers in parentheses are *p-values* from two-tailed tests.

Panel A: Changes in SFA-Based Relative Efficiency

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 *test statistic* (*p-value*)	Signed-rank test of Median *test statistic* (*p-value*)	Magnitude of Coefficient δ (*p-value*)
SALE	173	-0.017	-0.015	-4.31 (<0.0001)	-6295 (<0.0001)	1.12 (<0.0001)
GM	172	-0.065	-0.053	-8.65 (<0.0001)	-6406 (<0.0001)	4.62 (<0.0001)

Panel B: Changes in DEA-Based Relative Efficiency

Output Metric	Malmquist index of pure relative efficiency change (Post-IFRS adoption measure relative to pre-IFRS adoption measure)				
	Number of firms	Geometric Mean of firm-specific $MALM\_EFF_0$	Median of firm-specific $MALM\_EFF_0$	t-test of Mean=1 *test statistic* (*p-value*)	Signed-rank test of Median=1 *test statistic* (*p-value*)
SALE	173	1.005	1.00	0.32 (0.75)	291 (0.55)
GM	172	0.878	0.958	-3.76 (0.0002)	-2089 (0.0009)

Table 8 Additional Sensitivity Analyses

This table runs tests using the SFA-based estimates of operational efficiency analogous to those reported in Table 3 Panel A. Table 8 Panel A reports estimation results after eliminating the years 2008 and 2009. Panel B reports results from a specification that uses the R&D capitalization formula specified in the Amir, Lev and Sougiannis (2003) study. 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 C reports results where Goodwill and Other Intangible Assets excluding Goodwill are introduced as two additional input variables. Observations with negative Goodwill or negative Other Intangible Assets are deleted. Numbers in parentheses are *p-values* from two-tailed tests.

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 *test statistic* (*p-value*)	Signed-rank test of Median *test statistic* (*p-value*)	Magnitude of Coefficient δ (*p-value*)
SALE	242	0.009	0.007	3.24 (0.0014)	7077 (<0.0001)	-0.58 (0.0001)
GM	241	0.058	0.049	7.88 (<0.0001)	9062 (<0.0001)	-4.86 (<0.0001)

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 *test statistic* (*p-value*)	Signed-rank test of Median *test statistic* (*p-value*)	Magnitude of Coefficient δ (*p-value*)
SALE	244	0.041	0.038	14.44 (<0.0001)	14117 (<0.0001)	-2.22 (0.0028)
GM	243	0.062	0.053	8.34 (<0.0001)	9401 (<0.0001)	-5.62 (<0.0001)

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 *test statistic* (*p-value*)	Signed-rank test of Median *test statistic* (*p-value*)	Magnitude of Coefficient δ (*p-value*)
SALE	215	0.038	0.032	9.70 (<0.0001)	10330 (<0.0001)	-2.17 (<0.0001)
GM	214	0.066	0.054	7.21 (<0.0001)	6517 (<0.0001)	-5.16 (<0.0001)

Table 9 Comparison of Efficiency before and after FAS 86 adoption for the US Software Industry

In this table, a sample of 97 firms and 671 (670) firm-year observations in the US software industry (SIC codes 7371-7374) from 1981 to 1991 (excluding the adoption year1986) are used to estimate SFA-based operational efficiency when the output metrics are SALE (GM). 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. YEAR denotes the observation year, and it is included to control for any *Hicksian* temporal expansion of the frontier. All other variables are defined in Table 2. We use the Battese and Coelli (1995) approach that jointly estimates Equations (2) and (3) specified in Section 3.1. The z vector in Equation (3) contains only the indicator variable, FAS86ADOPT, that takes the value of 1 for each of the 5 years after the adoption of FAS 86 (1987-1991), and 0 for each of the 5 years before the adoption of FAS 86 (1981-1985). In this specification, a *negative* and significant coefficient δ on FAS86ADOPT would indicate a significant improvement in efficiency in the post-FAR 86 adoption period relative to the pre period. We also separately calculate average efficiency for the pre and post periods for each firm in our sample. We then calculate the change in efficiency for each firm as the average post-period efficiency estimate of the firm minus its own average pre-period estimate. We then test the significance of the mean (median) change in efficiency using a t-test (signed-rank test). A *positive* and significant mean or median value would indicate efficiency improvement in the post period. Numbers in parentheses are *p-values* from two-tailed tests.

Output Metric	Firm-specific change in efficiency (Post-FAS 86 adoption estimate minus Pre-FAS 86 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 *test statistic* (*p-value*)	Signed-rank test of Median *test statistic* (*p-value*)	Magnitude of Coefficient δ (*p-value*)
SALE	97	0.033	0.023	5.25 (<0.0001)	1409 (<0.0001)	-2.42 (0.0084)
GM	97	0.063	0.040	3.91 (0.0002)	929 (0.0001)	-4.95 (<0.0001)