Finanzwirtschaftliche Entscheidungen auf Grundlage der Jahresabschlussanalyse

Inaugural-Dissertation zur Erlangung des akademischen Grades

eines Doktors der Wirtschaftswissenschaft des Fachbereichs

Wirtschaftswissenschaft der Freien Universität Berlin

vorgelegt von

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Berlin, 2015

Tag der Disputation: 11. Dezember 2015

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Vorbemerkungen

Die vorliegende Dissertationsschrift wurde nach der Promotionsordnung des Fachbereichs Wirtschaftswissenschaft vom 16.07.2008 angefertigt. Die Dissertationsschrift wurde kumulativ nach der Ausführungsvorschrift für das kumulative Promotionsverfahren, welche der Promotionsausschuss des Fachbereichs Wirtschaftswissenschaft am 09.07.2008 verabschiedet hat, angefertigt.

Hierzu erkläre ich Folgendes:

1. In Teil 1 wird gem. § 9 Abs. 2 Buchstabe b der Promotionsordnung der thematische Zusammenhang der Einzelbeiträge dargestellt. Die zusammenhängende Darstellung enthält eine Einführung in die Problemstellung, erläutert die wesentlichen Forschungsfragen und fasst die grundlegenden Ergebnisse der Einzelbeiträge zusammen.

2. In die Einleitung wurde gemäß § 9 Abs. 2 Buchstabe b der Promotionsordnung vom 16.07.2008 eine tabellarische Übersicht aufgenommen, die den Anteil der Eigenleistung bei Artikeln, die in Ko-Autorenschaft entstanden sind, kenntlich macht.

3. Eingereichte und bereits veröffentlichte Fachartikel sind der Dissertation als Kopie beigefügt. Für noch nicht veröffentlichte Beiträge enthält die Dissertation die entsprechende Arbeitspapier- bzw. Manuskriptfassung.

4. Die eingereichten Fachartikel wurden entsprechend den Anforderungen gemäß Buchstaben a bis e der Ausführungsvorschrift für das kumulative Promotionsverfahren vom Mai 2013 ausgewählt.

5. Ich versichere, dass die Dissertation von mir selbstständig erstellt und der Eigenanteil bei Artikeln in Ko-Autorenschaft wahrheitsgemäß angegeben wurde. Die Arbeit hat keiner anderen Prüfungsbehörde vorgelegen.

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Teil 1: Thematische Einordnung der Forschungsbeiträge

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1. Einleitung

Die vorliegende Dissertationsschrift thematisiert das Ableiten wirtschaftlicher Entscheidungen auf Grundlage von Jahresabschlussanalysen. Die im Rahmen dieser Dissertation verfassten Einzelbeiträge widmen sich ausgewählten Fragestellungen der betriebswirtschaftlichen Finanz- und Rechnungslegungsforschung, deren thematischer Zusammenhang im nachfolgenden Kapitel eruiert werden soll. Tabelle 1 enthält hierzu eine Übersicht über die jeweiligen Einzelbeiträge, Informationen über die mitwirkende Ko-Autorenschaft sowie weitere Veröffentlichungsdetails.

Dem breiten Anwendungs- und Forschungsspektrum der Jahresabschlussanalyse geschuldet, lassen sich die Erkenntnisse und Implikationen der jeweiligen Forschungsbeiträge nicht trennscharf spezifischen Kategorien zuordnen, sondern tragen vielmehr zu dem aktuellen Kenntnisstand der Finanz- und Rechnungslegungsforschung bei. Die Selektion der jeweiligen Forschungsfragen ist jedoch nach einem schematischen Vorgehen unternommen worden, sodass sowohl neuste Erkenntnisse der aktuellen Forschung umfassend analysiert und hierauf aufbauend mit eigenen Untersuchungen bisher unbeantwortete Fragestellungen beleuchtet werden.

Das über Jahrzehnte vorherrschende Bild sah die Jahresabschlussanalyse als einen fundamentalen Bestandteil der Firmenbewertung, der diversen Interessensgruppen eines Unternehmens Erkenntnisse bezüglich der ökonomischen Situation des zu bewertenden Unternehmens vermitteln soll. Seit den frühen 1990er Jahren transformierte sich der Einsatz der Jahresabschlussanalyse von einem reinen Analysewerkzeug vergangener Geschäftstätigkeiten hin zu einem Prognoseinstrument, das Einschätzungen über die zukünftige Ertragslage eines Unternehmens geben soll.[1] Der erste Beitrag dieser Dissertationsschrift überblickt mittels einer narrativen Literaturübersicht diese Transformation der Jahresabschlussanalyse von einem ad hoc Evaluationsmodell hin zu einem pro forma Prognosemodell der zukünftigen Unternehmensertragslage und knüpft somit an den Forschungsstrang der aktuellen Literatur an, auf welchen die weiteren Artikel dieser kumulativen Dissertation aufbauen.

[1] Vgl. Nissim und Penman (2001), S. 109.

Tabelle 1: Übersicht, Einordnung und Abgrenzung der einzelnen Forschungsbeiträge

Titel	Ko-Autoren	Thema	Methode	Unterschungsgegenstand	Eigenanteil	Zeitschrift, Fundstelle
A Review of Financial Statement-Based Fundamental Analysis Research: Profitability Forecasting and the Role of Persistence, Growth and Conservatism	—	Forschungsübersicht der Jahresabschlussanalyse	Theorie: Literaturüberblick	Wissenschaftliche Studien zur Jahresabschlussanalyse der letzten 30 Jahre	100%	
Financial Statement-Based Forecasts and Analyst Forecasts of Profitability: The Effect of Mandatory IFRS Adoption	Pronobis, Paul Yohn, Teri	Verwendung der Jahresabschlussanalyse durch Analysten und mittels statistischer Prognosemodelle	Empirie: Datenanalyse	Statistisches Prognosemodell, Analystenprognosen	33%	Kelley School of Business Research Paper No. 15-9
Improving Profitability Forecasts with Information on Earnings Quality	—		Empirie: Datenanalyse	Statistisches Prognosemodelle, Analystenprognosen, Aktienpreise	100%	Diskussionsbeitrag des Fachbereichs Wirtschaftswissenschaft (FACTS), Freie Universität Berlin, Nr. 2015/16
Determinanten und Beständigkeit extremer Ergebnisprognosefehler von Finanzanalysten – Eine bilanzkennzahlenorientierte Analyse europäischer Unternehmen	—		Empirie: Datenanalyse	Extreme Prognosefehler von Analysten	100%	Corporate Finance 2014 (6), S. 253-262

Nachdem der Literaturüberblick bisherige Erkenntnisse der Prognoserechnung unter Zuhilfenahme der Jahresabschlussanalyse zusammengefasst und ausgewählte, offene Fragestellungen dieses Forschungsbereichs dargelegt hat, thematisieren die anschließenden Artikel mittels empirischer Untersuchungen, wie Analysten und Investoren die Jahresabschlussanalyse als ökonomische Entscheidungsgrundlage nutzen. Dabei stützt sich die zugrunde liegende Methodik der folgenden drei Beiträge auf die Analyse historischer Archivdaten.

Der zweite Beitrag geht insbesondere der Frage nach, ob neue gesetzliche und regulatorische Richtlinien, welche auf eine Erhöhung des Informationsgehalts von Jahresabschlüssen zielen, den Nutzen externer Adressaten steigern. Im Fokus steht hierbei die obligatorische Anwendung der International Financial Reporting Standards (IFRS) in allen europäischen Mitgliedsstaaten und anderen ausgewählten Ländern. Im Speziellen wird untersucht, ob die Umstellung von länderspezifischen Rechnungslegungsstandards auf IFRS mit einer verbesserten Prognosegenauigkeit von Analysten und statistischen, auf Rechnungslegungsinformationen basierten Modellen, assoziiert ist. Diese Umstellung von länderspezifischen Rechnungslegungsstandards auf die einheitlichen IFRS wird als eines der einflussreichsten Ereignisse für die Rechnungslegungsforschung der vergangenen Jahrzehnte angesehen.[2] Somit zielt der Forschungsbeitrag darauf ab, die Auswirkungen von IFRS auf die Informationsverarbeitung von Adressaten der Jahresabschlüsse für die Einschätzung künftiger Firmenprofitabilität nachzuweisen, welche unter anderem integraler Bestandteil von Rechnungslegungsinformationen ist.[3]

Im Gegensatz zum zweiten Beitrag, welcher die Auswirkungen exogener, regulatorischer Einflüsse untersucht, widmet sich der dritte Beitrag den Auswirkungen firmenspezifischer Eigenschaften und deren Auswirkung auf die jahresabschlussbezogene Prognoserechnung. Anhand eines bilanzkennzahlenbasierten Prognosemodells wird gezeigt, inwieweit Änderungen in der Qualität[4] von grundlegenden Bilanzkennzahlen des Jahresabschlusses (z.B. Umsatzerlöse, Vermögensstruktur, Jahresüberschuss etc.) die Prognosegenauigkeit von Jahresabschlussadressaten und Prognosemodellen beeinflussen.

Abschließend geht der vierte Beitrag der Frage nach, ob extreme Prognosefehler von Finanzanalysten, die in einigen Fällen mehrere hundert Prozent Abweichung aufweisen und oftmals von fortwährender Beständigkeit in den Folgejahren sind, durch bestimmte

[2] Vgl. Christensen et al. (2013), S. 147; Cascino und Gassen (2014), S. 243.
[3] Vgl. bspw. FASB (1980), S.2 ff.
[4] Der Begriff Qualität wird in diesem Zusammenhang in Anlehnung an Dechow et al. (2010), S. 344 definiert: Higher quality earnings provide more information about the features of a firm's financial performance that are relevant to a specific decision made by a specific decision-maker.

Unternehmenscharakteristika und Determinanten in Jahresabschlüssen erklärt werden können.

Somit ergänzen sich Forschungsbeitrag eins bis vier, indem sowohl theoretische Grundlagen bisheriger Studien aus der relevanten Fachliteratur kritisch beleuchtet werden, als auch firmeninterne Ursachen und externe Einflüsse auf die Prognosegenauigkeit der Jahresabschlussanalyse betrachtet werden. Dadurch ist die nachfolgende Dissertationsschrift der Schnittmenge von Finanz- und Rechnungslegungswissenschaften zuzurechnen, indem finanzwirtschaftliche Entscheidungen auf Grundlage von Rechnungslegungsinformationen untersucht werden.

Im anschließenden Kapitel wird eine thematische Verbindung zwischen dem Untersuchungsgegenstand der Dissertation und der bisherigen Literatur hergestellt, bevor darauffolgend eine ausführliche Erläuterung der Einzelbeiträge hinsichtlich ihrer Untersuchungsfrage, Methodik und ihres Forschungsbeitrages detailliert präsentiert wird.

2. Thematische Einordnung der Forschungsbeiträge anhand verschiedener Ziele der Jahresabschlussanalyse

Der Begriff der Jahresabschlussanalyse (engl. financial statement analysis) wird in der Literatur als Überbegriff für eine Vielzahl unterschiedlicher Anwendungen genutzt, welche die Verwendung von in Jahresabschlüssen veröffentlichten Informationen subsummieren. Dabei lassen sich die Zielgruppen dieser Informationen in interne und externe Adressaten unterteilen. Während externen Adressaten ausschließlich Informationen zur Verfügung stehen, die im Rahmen des Jahresabschlusses für die Allgemeinheit veröffentlich werden, haben interne Jahresabschlussanalytiker Zugriff auf zusätzliche Informationen. Das Forschungsziel der vorliegenden Dissertationsschrift ist es, Erkenntnisse über den Informationsgehalt von Jahresabschlussinformationen zu gewinnen, welche allen Adressaten gleichermaßen zur Verfügung stehen. Daher werden firmeninterne Informationen und andere Quellen als publizierte Jahresabschlüsse von den Untersuchungen dieser Dissertation ausgeschlossen. Um die Forschungsbeiträge in das nicht trennscharf abgegrenzte Feld der Jahresabschlussanalyse einzuordnen, wird zunächst eine unvollständige Kategorisierung der Aufgaben der Jahresabschlussanalyse vorgenommen. *Wahlen, Baginski und Bradshaw (2014)* sehen die Aufgaben der Jahresabschlussanalyse als ein Spannungsfeld zwischen (1) der Einschätzung von industrie- und makroökonomischen Bedingungen, (2) der Analyse der spezifischen Firmenstrategie, (3) der Anwendung und Qualität von Rechnungslegungsstandards und -informationen, (4) der Bewertung aktueller Profitabilität

und Risiken, (5) der Prognose zukünftiger Profitabilität und Risiken, sowie (6) der Bewertung der Firma. Hierzu stellt *Penman (2010)* fest, dass gerade die Unterpunkte (5) und (6), welche historisch tendenziell der Literatur der Finanzwissenschaften zugeordnet wurden, bedingt durch eine Vielzahl vornehmlich empirischer Untersuchungen zunehmend auch als Disziplinen der Rechnungslegungsforschung angesehen werden können. Insbesondere die Prognose künftiger Profitabilität auf Basis von Rechnungslegungsinformationen wurde in jüngster Zeit vermehrt untersucht. Argumentativ wird angebracht, dass das Rechnungslegungssystem bereits die Datengrundlage für die Bewertung der aktuellen Profitabilität und des aktuellen Risikos liefert. Dementsprechend wäre das nächste Glied der Kausalkette, das Wissen über die aktuelle Entstehung dieser Informationen in die Zukunft zu projizieren, und hierfür nicht ausschließlich mathematisch-statistische Verfahren[5] zu nutzen, wie es prädominierend in der Literatur der Finanzwissenschaften vorzufinden ist.[6] Eine Vielzahl von Artikeln widmet sich in diesem Zusammenhang der Untersuchung spezifischer Rechnungslegungsinformationen. Allerdings fehlt bis dato ein globaler Überblick, welcher die Ergebnisse aus der Vielzahl von Studien vereint. Daher ist die Zielsetzung des ersten Forschungsbeitrages dieser Dissertation kritisch und in narrativer Form die einflussreichsten Studien der letzten 30 Jahre bezüglich der Prognose künftiger Firmenprofitabilität zusammenzufassen. Ein Literaturüberblick kann durch strukturierte Analysen von meist empirischen Artikeln Erkenntnisse aus einem weitläufigen Forschungsfeld effektiv bündeln sowie durch das Betrachten des bisherigen Wissens auf einer Metaebene selbst neue Erkenntnisse generieren.[7]

Der zweite Beitrag adressiert primär die Anwendung und Qualität von Rechnungslegungsstandards und -informationen (Aufgabe 3 der Jahresabschlussanalyse) während der Einführung von IFRS in der Europäischen Union. Das Ziel dieser empirischen Studie ist die Quantifizierung der Veränderung des Informationsumfeldes externer Adressaten von Jahresabschlüssen, welche basierend auf Rechnungslegungsstandards und -informationen finanzwirtschaftliche Entscheidungen treffen. Bisherige Untersuchungen liefern hierzu unterschiedliche Ergebnisse.[8] Anhand eines neuen Untersuchungsdesigns folgert die Studie, dass die verpflichtende Einführung von IFRS in Mitgliedsstaaten der Europäischen Union den relativen Nutzen von Jahresabschlussinformationen im Kontrast zu nationalen Rechnungslegungsstandards nur dann erhöht, wenn die Umstellung auf Seiten der jeweiligen Länder stark forciert und kontrolliert wird. Darüber hinaus hat diese Studie auch Implikationen auf die Anwendungsfelder (4)-(6), indem nachgewiesen wird, dass durch

[5] Exemplarisch ist das ARIMA-Verfahren oder die Box-Jenkins-Methode zu nennen.
[6] Vgl. Penman (2010), S. 212 f.
[7] Vgl. Baumeister und Leary (1997), S. 311.
[8] Vgl. für Verbesserungen z.B. Gebhardt und Novotny-Farkas (2011) sowie Barth et al. (2012). Für Verschlechterungen vgl. z.B. Atwood et al. (2011).

qualitativ hochwertigere Bilanzinformationen nach der Umstellung auf IFRS aktuelle Firmenbewertungen und zukünftige Prognosen akkurater werden.

Der dritte Beitrag dieser Dissertationsschrift untersucht, ob Profitabilitätsprognosen durch die Qualität der ausgewiesenen Bilanzkennzahlen beeinflusst werden. Die Zielsetzung dieses Beitrages ist daher in erster Line auf Unterpunkt (5) gerichtet, der Prognose zukünftiger Profitabilität und Risiken. Jedoch werden für Unternehmensbewertungsmodelle meist Einschätzungen künftiger Gewinne benötigt. Genauere Prognosemodelle sind demnach ebenso für Unterpunkt (6) der Jahresabschlussanalyse von hoher Relevanz und tragen letztlich zu einer effizienteren Kapitalallokation von Investoren bei. Die hierfür verwendete Untersuchungsmethode ist in die positive Rechnungslegungsforschung einzuordnen und verwendet historische Unternehmensdaten US-amerikanischer Firmen.

Abschließend lässt sich der vierte und letzte Beitrag, welcher extreme Prognosefehler von Finanzanalysten untersucht, als Querschnitt der Kategorien (1)-(6) einordnen. Prognosen von Finanzanalysten repräsentieren eine ganzheitliche Informationsverarbeitung von Jahresabschlüssen sowie weiterer Informationsquellen, indem sie aus einer großen Menge verfügbarer Daten relevante Informationen synthetisieren und abschließend in reduzierter Form verbalisieren.[9] Daher fokussiert die letzte Studie die Zielsetzung, wie effizient externe Nutzer von Jahresabschlüssen dort enthaltene Informationen prozessieren und welche Eigenschaften starke Fehlprognosen induzieren.

[9] Vgl. Bouwman et al. (1987), S.1.

3. Forschungsfragen und -beiträge

3.1. A Review of Financial Statement-Based Fundamental Analysis Research: Profitability Forecasting and the Role of Persistence, Growth and Conservatism

Dieser Beitrag zielt in Form eines narrativen Literaturüberblicks darauf ab, die relevantesten Forschungsergebnisse des Bereichs der Prognoserechnung mittels Rechnungslegungsinformationen selektiv und strukturiert zu überblicken und darauf basierend wissenschaftlichen sowie praxisnahen Anwendern eine Übersicht zu gewährleisten, welche den aktuellen Forschungsstand dieses Bereichs komprimiert darstellt. In diesem Zuge werden ebenso bisher unbeantwortete Fragestellungen offengelegt, die zu der Weiterentwicklung des Verständnisses der Prognoserelevanz von Rechnungsinformationen beitragen würden. Ebenso werden bisherige Publikationen dieses Bereichs insbesondere unter den Aspekten ihrer empirischen Validität und ihres theoretischen Ansatzes kritisch diskutiert. Zuletzt wird die untersuchte Literatur auch danach analysiert, inwieweit derzeitige Prognoserechnungsmodelle rechnungslegungsspezifische Einflüsse, wie beispielsweise die Anwendung eines ausgeprägten Vorsichtsprinzips, für eine erhöhte Prognosegenauigkeit miteinbeziehen und gegebenenfalls danach korrigieren.

Der Literaturüberblick lässt sich in drei thematische Schwerpunkte untergliedern. Der erste Schwerpunkt erarbeitet eine Struktur, nach welcher die bisherigen Forschungsbeiträge nicht trennscharf kategorisiert werden. Diese Struktur ermöglicht es, sowohl die Komponenten der unterschiedlichen Prognosemodelle, als auch die technische Umsetzung zu überblicken. Dabei wird ersichtlich, dass erst in jüngerer Vergangenheit fundierte Rechnungslegungstheorien für Prognosemodelle verwendet werden, wohingegen zuvor statistische Auswahlkriterien die Selektion der Variablen determinierten. Ebenso wird dem Leser verdeutlicht, inwiefern sich die Jahresabschlussanalyse von einem reinen ad hoc Analyseinstrument hin zu einem Prognosemodell zukünftiger Geschäftsfähigkeiten über die letzten zwanzig Jahre entwickelt hat. Im Anschluss an diesen Überblick werden dann im zweiten Schwerpunkt die wichtigsten Forschungsbeiträge des Literaturüberblicks detailliert und kritisch analysiert. Hierfür werden auch weitere Forschungsfragen für zukünftige wissenschaftliche Untersuchungen identifiziert sowie Kritikpunkte der analysierten Studien dargelegt und diskutiert. Zuletzt zeigt eine Simulation im dritten Schwerpunkt auf, wie firmenspezifische Effekte Bilanzpositionen beeinflussen können und somit bei nicht zeitinvarianten Bedingungen die Genauigkeit von Prognosemodellen potentiell stören können. Auf diesen Erkenntnissen basierend verdeutlicht der Literaturüberblick, dass in der aktuellen Rechnungslegungsforschung solch störende Effekte umfassend untersucht, aber bisher unzureichend in Prognosemodellen verankert sind.

3.2. Financial Statement-Based Forecasts and Analysts Forecasts of Profitability: The Effect of Mandatory IFRS Adoption

Die Einführung der International Accounting Standards (IFRS) in Mitgliedsländern der Europäischen Union und diversen weiteren internationalen Staaten stellt eine der bedeutendsten und tiefgreifendsten Rechnungslegungsreformen der jüngeren Vergangenheit dar.[10] Zahlreiche empirische Untersuchungen haben die Auswirkungen der IFRS aus unterschiedlichen Blickwinkeln kritisch analysiert und konnten in diesem Zuge überwiegend positive Auswirkungen feststellen.[11] Obwohl einige Studien einen positiven Einfluss von IFRS auf die Beurteilung und Erfassung von Rechnungslegungsinformationen nachweisen können, was sich mitunter auf eine verbesserte Prognosegenauigkeit von Finanzanalysten auswirkt[12], herrschen im bisherigen Schrifttum unterschiedliche Meinungen bezüglich der Auswirkungen auf die Qualität von Bilanzinformationen[13] vor. Dieser Beitrag zielt daher darauf ab, anhand einer neuen Untersuchungsmethode der Frage nachzugehen, inwieweit durch die Einführung von IFRS die Qualität von veröffentlichten Rechnungslegungsinformationen beeinflusst wird und ob diese Auswirkungen auf Anwendungen und Adressanten von Jahresabschlüssen hat.

Zur Beantwortung dieser Fragestellung untersucht die Studie die Schätzgenauigkeit von Finanzanalysten und rechnungslegungsbasierten Prognosemodellen, welche die nächstjährige Profitabilität von börsennotierten Firmen aus 22 Ländern prognostizieren, die seit dem 1. Januar 2005 verpflichtet sind, konsolidierte Jahresabschlüsse nach IFRS aufzustellen. Als Vergleichsgruppe wird ein Datensatz mit US-Firmen herangezogen, die während des gesamten Untersuchungszeitraumes US-GAAP verpflichtend anwenden mussten.

Zunächst weist die Studie signifikante Verbesserungen der Prognosegenauigkeit von Finanzanalysten nach der Einführung von IFRS auf. Hingegen wird die Genauigkeit des rechnungslegungsbasierten Prognosemodells nur für diejenigen Firmen besser, welche sich in Ländern befinden, die während der Einführung von IFRS auch substantielle Veränderungen in ihrem regulatorischen Umfeld forcierten. Im Anschluss analysiert die Studie die Assoziation zwischen Analysten- und Modellprognosen und kommt zum Ergebnis, dass die Verbesserung der Analystenprognosen mit einer Umstellung auf IFRS mit einer Verbesserung der Modellprognosen assoziiert ist. Allerdings legen nachfolgende

[10] Ende 2014 erlauben oder verpflichten annähernd 120 Länder börsennotierten Unternehmen die Rechnungslegung unter IFRS. Hierfür haben annähernd 90 Länder vollständig als vorherrschenden Rechnungslegungsstandard adaptiert.

[11] Vgl. exemplarisch Brüggemann et al. (2013) und Soderstrom und Sun (2007) für einen umfassenden Literaturüberblick.

[12] Vgl. z.B. Byard et al. (2011), S. 69 ff. oder Horton et al. (2013), S. 388 ff.

[13] Vgl. z.B. Atwood et al. (2011), S. 103 ff. oder Barth et al. (2012), S. 68 ff.

Untersuchungen offen, dass Finanzanalysten in Abhängigkeit des regulatorischen Umfeldes Prognosemodellen mehr bzw. weniger Gewicht zukommen lassen. Zuletzt wird nachgewiesen, dass Analysten ihre Prognosegenauigkeit unabhängig vom regulatorischen Umfeld steigern könnten, da Prognosemodelle inkrementellen Informationsgehalt zusätzlich zu den Analysteneinschätzungen besitzen.

Die Studie liefert insbesondere wichtige Implikationen für die Forschungsgebiete der rechnungslegungsbasierten Prognoserechnung und die der Normierung von Rechnungslegungsstandards. Die Ergebnisse zeigen nicht nur die Auswirkungen von IFRS auf Analysten- und Modellprognosen, sondern geben darüber hinaus Indikation, dass einer mit IFRS einhergehenden Rechnungslegungsqualität Mitverantwortung für diese positiven Effekte zuzuschreiben ist.

3.3. Improving Profitability Forecasts with Information on Earnings Quality

Nach aktuellen Erkenntnissen aus der empirischen Rechnungslegungsforschung besitzen ausgewählte Bilanzkennzahlen inkrementellen Informationsgehalt bezüglich der Prognose zukünftiger Unternehmensprofitabilität.[14] Unabhängig von diesen Erkenntnissen weist der Forschungsbereich bezüglich der Ergebnisqualität von Bilanzinformationen (engl. earnings quality) nach, dass gewisse Bilanzkennzahlen temporär, wie auch latent, insbesondere durch die eigentliche Unternehmensleistung und die Ausgestaltung des Rechnungslegungs-systems beeinflusst werden.[15] Demnach besitzen Bilanzkennzahlen eine höhere Ergebnisqualität, wenn sie mehr Informationen über die wirtschaftliche Lage eines Unternehmens beinhalten und dadurch einen höheren Entscheidungsnutzen vermitteln.[16] Die Zielsetzung dieses Beitrages ist es, durch ein empirisches Untersuchungsdesign festzustellen, ob eine durch Ergebnisqualität induzierte Volatilität in Bilanzinformationen rechnungslegungsbasierte Prognosemodelle beeinflusst. Hierfür werden aktuelle Erkenntnisse aus den Forschungsbereichen der Ergebnisqualität und der Bilanzkennzahlen basierten Prognoserechnung zusammengeführt. Die Entwicklung akkuraterer Prognosemodelle, was die Zielsetzung dieses Beitrages ist, besitzt sowohl für wissenschaftliche, als auch für praxisnahe Anwendungen hohe Relevanz. Exemplarisch zu erwähnen sind die Bereiche der Unternehmensbewertung und Kapitalallokation, in welchen Annahmen über die zukünftige Wertentwicklung von Unternehmen getroffen werden müssen.

[14] Vgl. z.B. Fairfield und Yohn (2001), S. 371 ff.; Mohanram (2005), S. 133 ff; Piotroski und So (2012), S. 2841 ff.
[15] Vgl. Barth et al. (2008), S. 468.
[16] Vgl. Dechow et al. (2010) für einen umfassenden Überblick über Ergebnisqualität in der Rechnungslegungs-forschung.

Zur Beantwortung der Fragestellung wird zunächst mit einem Datensatz von 17,808 US-amerikanischen Unternehmen die Assoziation zwischen Bilanzkennzahlen und künftiger Unternehmensprofitabilität (12-Monate Prognose) analysiert. Die Studie verwendet hierfür zwei Modelle: Das erste Modell verwendet Bilanzkennzahlen der DuPont-Analyse, welche nach aktueller Forschung inkrementellen Erklärungsgehalt für zukünftige Firmenprofitabilität[17] besitzt. Das zweite Modell baut auf dem vorigen auf, ergänzt dieses aber mit erklärenden Variablen der aktuellen Ergebnisqualität eines Unternehmens. Durch Interaktion der Bilanzkennzahlen mit den Ergebnisqualitätsvariablen weist der Forschungsbeitrag nach, dass die Prognosegenauigkeit künftiger Unternehmensprofitabilität durch die Qualität der ausgewiesenen Rechnungslegungsinformationen beeinflusst wird. Für eine Quantifizierung der Verbesserung der Prognosegenauigkeit werden für beide Modelle anschließend sog. Out-of-sample-Prognosen kalkuliert. Hierfür werden mit einer rollenden Regression geschätzte Koeffizienten der DuPont-Analyse und Ergebnisqualitätskennzahlen in einem fortwährenden Fünfjahresintervall berechnet und für die Prognose der Profitabilität des jeweils nächsten Jahresabschlusses verwendet. Dieses Verfahren weist nach, dass das Hinzufügen von Ergebnisqualitätskennzahlen die Prognosegenauigkeit der normalen DuPont-Analyse signifikant verbessert. Weitere Regressionsanalysen zeigen darüber hinaus, dass das in diesem Beitrag vorgeschlagene Vorgehen Ergebnisqualität für Prognosezwecke zu einem gewissen, statistisch signifikantem Grad erfassen kann.

Zudem wird nachgewiesen, dass Kapitalmarktteilnehmer (Finanzanalysten und Investoren) Ergebnisqualitätsinformationen für ihre finanzwirtschaftlichen Entscheidungen berücksichtigen. Empirische Ergebnisse indizieren, dass Ergebnisprognosen von Finanzanalysten einen statistisch stärken Zusammenhang mit Modellen aufweisen, welche Informationen bezüglich der Ergebnisqualität eines Unternehmens ausweisen. Analysen der Kaufentscheidungen von Aktieninvestoren zeigen zusätzlich, dass Marktteilnehmer ebenfalls Ergebnisqualitätsinformationen für ihre Kapitalallokation berücksichtigen. Dadurch kann eine simple Anlagestrategie, die auf einer um Ergebnisqualitätsinformationen ergänzte DuPont-Analyse basiert, keine abnormalen Kapitalmarktrenditen erwirtschaften.

3.4. Determinanten und Beständigkeit extremer Ergebnisprognosefehler von Finanzanalysten – Eine bilanzkennzahlenorientierte Analyse europäischer Unternehmen

Ergebnisprognosen von Finanzanalysten werden in der Finanz- und Rechnungslegungsforschung seit mehreren Jahrzehnten intensiv beleuchtet.[18] Dieser

[17] Firmenprofitabilität wird hier als Return on Net Operating Assets (RNOA) gemessen.
[18] Vgl. Healy und Palepu (2001), S. 405 ff.

Beitrag setzt sich mit Ergebnisprognosefehlern von Finanzanalysten auseinander, konzentriert sich dabei aber auf sog. extreme Prognosefehler. Ein extremer Prognosefehler wird dadurch definiert, dass er sich in den äußeren Bereichen[19] der Gesamtverteilung aller Analystenprognosefehler befindet und damit in einigen Fällen eine Abweichung von mehreren hundert Prozent aufweist. Bisher hat die einschlägige Literatur solchen extremen Prognosefehlern nur unzureichend Beachtung geschenkt und hat diese sogar oftmals zur Steigerung der statistischen Güte von Untersuchungen ausgeschlossen. Daher verfolgt der Beitrag in einem ersten Schritt die Zielsetzung, den Begriff des extremen Prognosefehlers in der Literatur zu Finanzanalysten zu etablieren sowie auf dessen Implikationen einzugehen. Über einen zeitlichen Verlauf von fünfzehn Jahren (1999-2014) wird die Entwicklung des Unterschiedes von extremen zu nicht-extremen Prognosefehlern dokumentiert. Anschließend geht der Beitrag der Frage nach, ob spezifische Firmencharakteristika die Wahrscheinlichkeit eines extremen Prognosefehlers determinieren.

Die empirische Untersuchung verwendet Finanzanalystenprognosen für über 20.000 europäische Unternehmensbeobachtungen, was einer Gesamtanzahl von über 140.000 individuellen Prognosen entspricht. Der Beitrag verdeutlicht zunächst die hohe Ungenauigkeit von extremen Prognosefehlern im Vergleich zum arithmetischen Mittelwert des gesamten Untersuchungszeitraums. Dabei liegt die durchschnittliche höhere Abweichung von extremen Überschätzfehlern bei 230% (44% für Unterschätzer). Eine Analyse diverser Firmencharakteristika legt dar, dass Finanzanalysten vor allem Unternehmen, die hohe Profitabilitätsschwankungen aufweisen und in einem volatilen Marktumfeld agieren, schlechter beurteilen können. Die Wahrscheinlichkeit extremer Prognosefehler wird dadurch erhöht. Eine Profitabilitätsanalyse mittels einer DuPont-Analyse zeigt darüber hinaus, dass ein hoher Ergebnisprognosefehler auch durch einbrechende Kapitalrendite entsteht.

Abschließend wird die Beständigkeit extremer Prognosefehler in den Folgejahren ausgewertet. Eine Analyse des zeitlichen Verlaufs der Analystenschätzer verdeutlicht, dass diese auch im Folgejahr nach einer extremen Fehleinschätzung ihre Prognosen nur unzureichend adjustieren. Damit weisen extreme Ergebnisprognosefehler eine hohe Beständigkeit auf.

[19] 10. bzw. 90. Perzentil

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Zusammenfassung

Bei der vorliegenden Arbeit handelt es sich um eine kumulative Dissertation, welche sich aus vier Einzelbeiträgen zusammensetzt. Hierbei ist das Themenfeld der Jahresabschlussanalyse und ihre Relevanz für finanzwirtschaftliche Entscheidungen der zentrale Forschungsrahmen der Einzelbeiträge. Die Arbeit ist so aufgebaut, dass zunächst eine thematische Einordnung der Einzelbeiträge dieser Dissertation sowie eine Übersicht über die Forschungsfragen vorgenommen werden. Im Anschluss werden die Einzelbeiträge präsentiert.

Der erste Beitrag analysiert umfassend und diskutiert kritisch Forschungsergebnisse zur rechnungslegungsbasierten Prognoserechnung der letzten Jahrzehnte. Die dabei gewählte Methodologie ist ein narrativer Literaturüberblick, der die relevante Literatur zunächst strukturiert, anschließend diskutiert und darauf basierend bisher unbeantwortete Fragestellungen offenlegt. Des Weiteren wird mittels einer Simulation und einer Analyse der Literatur aufgezeigt, wie Rechnungslegungsinformationen durch firmenspezifische Effekte (insb. Wachstum, Vorsichtsprinzip und Beständigkeit von ausgewiesenem Jahresgewinn) beeinflusst werden und dadurch die Genauigkeit von Prognosemodellen mindern können.

Der zweite Beitrag geht mittels empirischer Untersuchungen der Frage nach, ob die Einführung der IFRS mit einer Erhöhung der Genauigkeit von rechnungslegungsbasierten Prognosemodellen assoziiert ist. In diesem Zuge wird ebenfalls analysiert, inwieweit die Prognosegenauigkeit von Finanzanalysten von dieser Umstellung profitiert und ob diese Veränderung auf rechnungslegungsbasierte Prognosemodelle zurückzuführen ist. Die Studie zeigt, dass eine Veränderung der Prognosegenauigkeit sowohl von Finanzanalysten, als auch von Prognosemodellen von Veränderungen im regulatorischen Umfeld der jeweiligen Länder abhängt. Die Ergebnisse deuten darauf hin, dass rechnungslegungsbasierte Prognosen auch nach einer Umstellung auf IFRS zusätzlichen Erklärungsgehalt für künftige Unternehmensprofitabilität liefern.

Der dritte Beitrag beleuchtet den Einfluss der Ergebnisqualität (earnings quality) eines Unternehmens auf rechnungslegungsbasierte Prognosemodelle. Die Studie erarbeitet zunächst ein Modell, welches Einflussfaktoren von Ergebnisqualität in Prognosemodelle miteinbezieht. Eine anschließende empirische Auswertung deutet darauf hin, dass eine solche Modellerweiterung die Prognosegenauigkeit für künftige Unternehmensprofitabilität verbessert. Allerdings scheinen Kapitalmarktteilnehmer Einflüsse von Ergebnisqualität bereits in ihre Entscheidungsgrundlage für Kapitalallokationen miteinzubeziehen.

Der vierte und letzte Beitrag untersucht extreme Prognosefehler von Finanzanalysten. Ein extremer Prognosefehler wird dadurch definiert, dass er sich in den äußeren Bereichen der Gesamtverteilung aller Analystenprognosefehler befindet und damit in einigen Fällen eine Abweichung von mehreren hundert Prozent aufweist. Eine empirische Auswertung von Archivdaten europäischer Unternehmen verdeutlicht, dass firmenspezifische Charakteristika, wie beispielsweise die Industriezugehörigkeit, die Wahrscheinlichkeit solcher extremen Prognosefehler beeinflussen. Auch im Folgejahr eines extremen Prognosefehlers scheinen Finanzanalysten ihre Prognosen nicht korrigieren zu können, so dass dieser Fehlertyp eine hohe Beständigkeit aufweist.

Summary

This cumulative dissertation thesis consists of four studies. The main research topic of all studies analyzes the usefulness of financial statement analysis for making financial decisions. The dissertation thesis is organized as follows: the first part classifies all four studies into the research stream of financial statement analysis. Furthermore, an overview is provided that summarizes the research questions. The second part of the thesis presents the respective studies.

The first study comprehensively surveys the financial statement analysis research of the past decades. First, this narrative literature review suggests a structure to categorize research within this literature stream. Subsequently, I critically discuss findings and show future research opportunities which would further advance this research field. A simulation documents how accounting specific effects influence forecasts and how they could decrease forecasts' accuracy.

The second study examines whether mandatory IFRS adoption is associated with an increase in the accuracy of financial statement-based models for forecasting profitability. The study also examines the relation between analyst forecast accuracy and financial-statement-based forecast accuracy around mandatory IFRS adoption. Our findings suggest that changes in the forecast accuracy of analysts and financial statement-based models depend on the regulatory environment of the respective countries. The results further indicate that financial statement-based forecasts provide incremental information over analyst forecasts for explaining future profitability for firms in countries that mandatorily adopted IFRS.

The third study sheds light on the influence of earnings quality on forecast accuracy of financial statement based forecasting models. The study proposes a model that incorporates the influence of earnings quality into profitability forecasts. Empirical analyses suggest that such an enhanced model improves the forecast accuracy of profitability one year-ahead. However, market participants seem to properly include influences from earnings quality in their investment decisions.

The fourth and last study analyzes extreme forecast errors of financial analysts. Extreme forecasts errors are defined as predictions with extensive forecast dispersion. By examining a comprehensive data sample of European firms and analysts' forecasts, the article empirically investigates firm characteristics based on a wide range of disclosure information. The analysis also shows that firms with high forecast dispersion tend to operate in a volatile market environment. Likewise, analysts do not appear adjusting forecasts efficiently in the year after an extreme estimation error. As a consequence, extreme forecast errors exhibit a significant persistence.

Überblick über die Einzelbeiträge

Beitrag 1: A Review of Financial Statement-Based Fundamental Analysis Research: Profitability Forecasting and the Role of Persistence, Growth and Conservatism, Working Paper.

Beitrag 2: Forecasts of Profitability and Analysts' Forecast Errors: Change due to Mandatory IFRS Adoption, Kelley School of Business Research Paper No. 15-9 (mit T. Yohn und P. Pronobis).

Beitrag 3: Improving Profitability Forecasts with Information on Earnings Quality, FACTS Discussion Paper, School of Business & Economics, FU-Berlin, Nr. 2015/16.

Beitrag 4: Determinanten und Beständigkeit extremer Ergebnisprognosefehler von Finanzanalysten – Eine bilanzkennzahlenorientierte Analyse europäischer Unternehmen, in: Corporate Finance 2014 (06), S. 253-262.

Teil 2:

A Review of Financial Statement-Based Fundamental Analysis Research:

Profitability Forecasting and the Role of Persistence, Growth and Conservatism

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A Review of Financial Statement-Based Fundamental Analysis Research:

Profitability Forecasting and the Role of Persistence, Growth and Conservatism

Abstract

This study reviews the recent financial statement-based fundamental analysis (FSA) literature on profitability forecasting. The first part of the review highlights that financial forecasting is a matter of accounting rather than an exclusive province of finance. The detailed analysis shows that the structure of financial statement-based forecasts has shifted from *unstructured* forecasting models, to more *structured* approaches, and finally towards *theory-driven* models that incorporate latest findings from accounting research. In the second part, a Monte Carlo simulation documents how earnings persistence, growth and conservatism affect a firm's future firm value through changes in profitability. Here, I draw the forecast dispersion that could emerge from the interaction between fundamental performance and the configuration of the accounting system. Surprisingly, I find that the current literature does not pay full attention with respect to earnings persistence, growth and conservatism as it frequently neglects their incorporation in forecast models. The study concludes with future research opportunities which would further advance this important field of research.

Keywords: financial statement analysis, forecasts, profitability, growth, conservatism

JEL classification: M41, G17

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1. Introduction

The intrinsic value of a firm is theoretically determined by future dividend payoffs (see hereto, for instance, Rubinstein 1976; Brealey et al. 2013; Copeland et al. 2010; Lundholm and Sloan 2012; Penman 2012). Depending on the forecasting model, analysts have to select which predictor they use in a forecast for future payoffs. The selection of these predictors as well as the valuation process has traditionally been the province of finance literature. However, while the finance literature has enormously progressed in the area of asset pricing by a structured analysis of risk and expected returns (e.g. Capital Asset Pricing Model, 3-Factor Model, Momentum etc., see Fama and French 2004 for an overview), valuation techniques based on future dividend payoffs have not advanced much beyond applying the dividend discount model (Nissim and Penman 2001). In addition, some major concerns come with a primary focus on dividend forecasts. First, dividends are determined by the underlying dividend payout policy and are not unconditionally anchored to the periodic performance of a firm. That is, forecasted dividend payoffs are regularly detached from a firms' economic performance (see Penman 1992). Second, current dividend payoffs are usually not linearly associated with future dividend payoffs and are, thus, hard to predict with statistical approaches (see Beaver 1989).

In contrast, financial statement-based fundamental analysis research (FSA) tends to infer the value of a firm without regard to future dividend payoffs or stock prices that reflect market sentiments about current and future equity value (see Wahlen et al. 2011). Instead, FSA uses published financial reports and other relevant information concerning the economic environment of businesses to assess their intrinsic value (see Mohanram 2005). For publicly traded firms, one subsequently contrasts the estimated intrinsic value with the traded market value of firm's equity (see Piotroski and So 2012). The correlation between the intrinsic value and the market value is finally used to facilitate investment decisions along with other criteria such as risk factors. Understanding the determinants of value, FSA also facilitates evaluating non-publicly traded firms (see Penman 2012).

However, the FSA literature has long been criticized for presenting ad-hoc statistical correlations without a theoretical foundation, and thus, 'has to move beyond reporting descriptive statistics and evidence of the success of trading strategies into proposing theories and presenting empirical tests of the hypotheses derived from the theories' (Kothari 2001, p. 173). However, Kothari's (2001) review is over a decade old and the FSA literature has progressed tremendously since then.

Since the early 1990s, an increasing stream within the accounting research literature elaborates on the idea that financial forecasting and firm valuation are also a matter of accounting. In particular, the Ohlson (1995) and the Feltham and Ohlson (1995) studies provide a foundation for redefining the research on the relation between firm value and financial statement information. Both studies stand among the most important developments in accounting research and provide a theoretical structure for modeling the relationship between accounting information and firm valuation (Bernard 1995). The Feltham-Ohlson model (hereafter F-O model) approximately states that the value of a firm can be modeled over a finite horizon as a function of forecasted earnings, book value, and a discount rate. The model assumes that forecasts are consistent with the clean surplus relation in order to justify the replacement of dividends by future earnings and book value. This is appealing for two reasons in particular: first, by focusing on financial statement information, forecasts are built on accounting equations that follow a predefined structure in comparison to dividend payout policies that are a result from a broader set of circumstances. Second, shifting the forecast objective to FSA ratios enables researchers to discover new factors that explain current value and future firm performance. Studies can offer evidence whether FSA ratios add incremental information for explaining future earnings or book value. Predicting future payoffs with accounting ratios thus becomes a building block system where relevant value drivers have to be separated from those that do not add further information. Penman (2010) summarizes that FSA forecasting involves accounting for the future instead of just analyzing historic business processes.

Consequently, the assignment of the present study is to review the recent FSA literature on the usefulness of accounting information for forecasting firm performance. The stance taken in this survey is that research within this area has developed in an unorganized manner rather than in a consecutive evolution process where each study has incrementally added insights on how accounting ratios can be used to forecast future payoffs. As such, this study develops a structure to provide researchers and practitioners, who intend to evaluate the properties of accounting ratios in forecasting models, an organized framework. Furthermore this study should help to guide through prior research findings and to identify unresolved issues for future research. I also critically discuss effective and ineffective use of accounting ratios for investigating questions related to the predictive character of accounting information. Associated with this, I also address validity issues that could arise from both forecasting models and performance measurements. Given the great number of FSA studies in the recent past, however, I try to identify the most contributing studies and some of their key issues, but

I do not attempt to be comprehensive. Finally and given the existence of several literature reviews of related topics in the field of capital market research in accounting, I focus on studies that mainly examine the relation between accounting information and the estimation of future firm performance measured as earnings and/or stock returns (e.g. Bauman 1996; Kothari 2001; Beaver 2002; Richardson et al. 2010; Lewellen 2010).

The paper proceeds as follows. Section 2 reviews the existing empirical research. Section 3 sheds light on persistence, growth, and conservatism as the key influencing factors that could have significant impact on the accuracy of FSA forecasts. Finally, Section 4 summarizes the paper and identifies areas for additional research.

2. Financial Statement-Based Fundamental Analysis Research into Profitability Forecasting

2.1 Classification of Types of Financial Statement-Based Fundamental Analysis Research

Financial statement-based fundamental analysis research into profitability forecasting has long been practiced without any theoretical framework (e.g. Lipe 1986; Ou and Penman 1989; Ou 1990; Lev and Thiagarajan 1993; Fairfield et al. 1996). These types of studies incorporate financial statement-based ratios for profitability forecasting on the basis of statistical properties and/or practice-oriented criteria. Accordingly, the underlying assumptions with respect to the relation between current financial statement information and future performance are generally ad hoc. I refer to these types of studies as *unstructured profitability forecasting approaches* due to the fact that there exist no guidelines around which could serve as a structure for financial statement analysis.

On the contrary, structural approaches build upon financial statement analysis as a way to identify and to organize relevant financial statement-based ratios in a hierarchical order.

Financial statement-based ratios lower in the ordering are identified to provide finer information for the forecasting task than those higher up. The identification of future profitability drivers thereby distinguishes between ‘permanent’ and ‘transitory’ features of financial statement-based ratios. In addition, traditional DuPont analysis usually provides the algebra for how financial statement-based ratios ‘sum up’ as

building blocks of future profitability as well as for how financial statement-based ratios should be structured hierarchically (sees Nissim and Penman 2001). Consequently, I refer to these type of studies as *structured profitability forecasting approaches*.

Finally, following the accounting valuation model development from Ohlson (1995) and Feltham and Ohlson (1995), fundamental analysis research has moved toward a more theory-based approach. Essentially, this model is a statement that book value and earnings are relevant valuation attributes (Bauman 1996). In particular, book value represents a stock measure of value while earnings measure increments to book value and thus represents a flow measure of value. The model also highlights the existence of other (financial and non-financial) information likely to be relevant for profitability forecasting. The identification of such information builds upon economic theory and requires institutional knowledge. I refer to those studies that incorporate financial statement-based ratios and other information on the basis of economic theory and institutional knowledge as *theory-driven profitability forecasting approaches*.

2.2 Unstructured Profitability Forecasting Approaches

As outlined above, early profitability forecasting approaches used financial statement-based ratios in an ad hoc manner without referring to economic theory, institutional knowledge or any kind of hierarchical structure. Nevertheless, these kinds of studies have contributed to an advancement of the field by providing a comprehensive overview of the predictive power of a wide range of financial statement-based accounting ratios (Penman 1992)[20]. I follow the work of Pinches et al. (1973) to provide some structure to the large number of financial statement-based ratios.[21] Applying factor analysis to isolate independent patterns of financial statement-based ratios, Pinches et al. (1973) developed seven empirically-based taxonomies which retain the maximum amount of information from the original data matrix. These taxonomies (hereafter PMC categories) are (1) Return on Investment, (2) Capital Intensiveness, (3) Inventory Intensiveness, (4) Financial Leverage, (5) Receivables Intensiveness, (6) Short-term liquidity, and (7) Cash Position. The following survey is based on the 19 studies that apply an *unstructured profitability forecasting approach*. These studies include: Ou and Penman (1989), Ou (1990), Lev and Thiagarajan (1993), Stober (1992), Abarnell and Bushee (1997) Setiono and Strong (1998), Al-

[20] According to Penman (1992, p. 471): 'the task of research is to discover what information projects future earnings and, from a financial statement analysis point of view, what information in the financial statements does this.'

[21] Some studies provide analyses including over 100 financial statement-based ratios (e.g., Gombola and Ketz 1989a, 1989b; Chen and Shimerda 1981).

Debie and Walker (1999), Martinez (1999), Piotroski (2000), Beneish et al. (2001), Chung and Kim (2001), Dowen (2001), Swanson et al. (2003), Mohanram (2005), Skogsvik (2008), Alexakis et al. (2010), Noma (2010), Piotroski and So (2012) and Seng and Hancock (2012).

As provided by Table 1, I note several interesting findings with respect to the distribution of financial statement-based ratios used for profitability forecasting along the Pinches et al.'s (1973) taxonomy framework. First, the studies are fixated on 'Return on Investment' [22] , 'Capital Intensiveness'[23] and 'Inventory Intensiveness'[24] metrics although early financial statement-based fundamental analysis research emphasizes a diversification of ratios to be used for forecasting purposes (e.g. Oppenheimer 1984). These three taxonomies can be found in 100 %, 94.7 %, and respectively, 73.7 % of the studies. In contrast, the 'Financial Leverage' and 'Receivable Intensiveness' are less represented in the studies under review. While the 'Financial Leverage' and the 'Receivable Intensiveness' metrics can be found in 42.1 % of the studies examined, the 'Short-Term Liquidity' metrics are only included in 36.8 % of these studies. Finally, 'Cash Position' metrics can just be found in 10.5 % of the examined studies.

[22] Commonly used ratios are net income/total assets, earnings before interest and taxes (EBIT)/total assets, EBIT/sales, earnings before taxes (EBT)/sales, net income/book value of equity, or net income/total assets etc.
[23] For instance, working capital/assets, sales/total assets, cost of goods sold/inventories, or current liabilities/net plants etc.
[24] For instance, working capital/total assets, inventory/sales, or sales/working capital etc.

TABLE 1

Analysis of accounting ratios used in unstructured profitability forecasting approaches

Ranking	*Ratio Categories (Most frequently ratio)*	*Percentage*
1	Return on Investment (Return on Equity)	100.0%
2	Capital Intensiveness (CAPEX / Total Assets)	94.7%
3	Inventory Intensiveness (Inventory Turnover)	73.7%
4	Financial Leverage (Dept / Equity)	42.1%
5	Receivables Intensiveness (Receivables / Sales)	42.1%
6	Short-term Liquidity (Current Ratio)	36.8%
7	Cash Position (Working Capital / Total Assets)	10.5%

Notes:
This table ranks the frequency of applied PMC categories in forecast models of unstructured profitability forecasting approaches. For this, all used accounting ratios in forecast models of nineteen studies (see list of studies above) were analyzed and sorted by the respective PMC categories. The right column gives the percentage share of each PMC category. If a study uses at least one ratio out of a certain category, this study takes the value of 1 for this category. The percentage share is then the total sum of studies that use the respective category divided by the total sum of all studies (19).

The study of Ou and Penman (1989) (hereafter O-P) begins with an analysis of 68 financial statement-based ratios. In order to reduce this set to a manageable quantity, they use statistical approaches similar to Pinches et al. (1973). But instead of applying a factor analyses, O-P use two logit models. The first univariate logit model includes each descriptor as the sole explanatory variable. In a second step, they reexamine all descriptors in a multivariate analysis and drop those that were not significant at the 10% level. Afterwards, they test the explanatory power of the left ratios for their earnings prediction model for two historical timeframes (1965-72 / 1973-77) by using 16 and 18 statistically significant accounting ratios, respectively. Only six variables appear in both models. O-P only find six out of seven ratios from the PMC categories to be useful for predicting earnings one year-ahead. No descriptor covered section (5), Receivables Intensiveness. At the same time, several categories are

represented by similar ratios (e.g. seven descriptors fall within category (3) Capital Intensiveness) what adds redundant information to their forecasting model.

Ou (1990) applies the same methodology to examine the information content of non-earnings accounting descriptors. The forecasting model retains eight non-earnings ratios in order to predict future earnings. The results stand in line with the original O-P framework. Although both studies rely on the same forecasting approach, they find different accounting ratios to be relevant. This fact shows two common threads of studies using an *unstructured profitability forecasting approach*. First, randomly assembled arrays of accounting ratios depend on the firm specific data set. Second, statistical associations can vary over time. Ratios that were found to be value-relevant in one sample period can lose their information content in the subsequent sample period. This effect impairs the external validity of such forecasting approaches. Nevertheless, O-P report impressive hedge returns (without further adjustments) of 12.5% in two-year hold-out samples. These findings attracted a great deal of attention in the literature (Kothari 2001).

Due to the seminal character of the O-P study, several papers extend this unstructured forecasting approach to analyze and predict market returns. Since this review mainly focuses on earnings predictions, I just briefly discuss these studies for the sake of completeness. Stober (1992) further distinguishes between the information contained in the O-P forecasting model and in analysts' forecasts of earnings. He attests a slight superiority of analysts' predictions over the FSA model. Stober (1992) confirms O-P findings by demonstrating that investors could experience abnormal returns up to six years following the portfolio formation if the FSA forecast and analysts' forecast disagree. This suggests that financial ratios capture information that is slowly recognized by the market.

Holthausen and Larcker (1992) partially mitigate some contingent sources of risk to the extent that abnormal returns are measured according to the CAPM, size-adjusted, and market-adjusted return metrics. The authors use the O-P framework to predict one year-ahead excess returns. Holthausen and Larcker's (1992) results suggest that reported stock market returns depend on the respective metric of measuring returns. Depending on the method, returns are much smaller (between 4.3% and 9.5%) as reported by O-P. Nevertheless, these hedge returns are still significantly higher than the market-wide average. Likewise, Greig (1992) confirms the measurement problem of market returns by re-examining the O-P study. After controlling for firm size, the relation between the FSA forecast and stock returns is

insignificant and negative. This finding shows that the strategy is not as robust as originally suggest by O-P.

In contrast to a purely statistical approach, studies like Lev and Thiagarajan (1993) as well as Abarbanell and Bushee (1997, 1998) follow a 'guided' selection of financial ratios. By extracting 'value relevant' accounting ratios suggested by professional analysts, they arrange forecasting models on the basis of well diversified accounting ratios. [25] The ratios used in these studies cover four out of seven PMC categories. They do not cover ratios for the Financial Leverage, Short Term Liquidity, and Cash Position. However, the research design of these studies is augmented with other financial statement information such as labor force or the use of LIFO/FIFO accounting methods. All three studies find the set of accounting descriptors as incrementally value-relevant, adding approximately 70% to the overall explanatory power beyond earnings. Nevertheless, the selection process of descriptors is opaque if one considers the vast variety of financial ratios suggested and applied in the fundamental analysis literature.

Similar to studies from the finance literature (e.g. Lakonishok et al. 1994; La Porta 1996; La Porta et al. 1997; Fama and French 1992; 2000, among others), Piotroski (2000) and Piotroski and So (2012) examine stock returns of high book-to-market firms ('value stocks') compared to low book-to-market firms ('glamour stocks'). These studies develop an aggregated statistic measure - the 'FSCORE' - that comprises nine financial ratios. According to the PMC categories, the FSCORE measures 4 out of 7 dimensions: (1) Return on Investment, (2) Capital Intensiveness, (3) Financial Leverage, and (6) Short Term Liquidity. Each financial signal is binary coded either as a positive or a negative indication for future abnormal returns and finally added up to the FSCORE (ranging from zero to nine). Piotroski 2000 finds that the particular combination of value stocks (glamour stocks) and high FSCOREs (low FSCOREs) gains abnormal returns.[26] As a consequence of this noticeable success, subsequent publications modify the original model into several modifications. Mohanram (2005) creates the 'GSCORE' that is specialized to identify firms with sustainable growth in low book-to-market portfolios. By shifting the focus on growth firms in particular, the GSCORE does not incorporate financial ratios for Financial Leverage and Short Term Liquidity, like the original model from Piotroski suggests. Growth firms tend to be more levered than established firms (see e.g. Myers 1984).

[25] Lev and Thiagarajan (1993) use 12 variables whereas Abarbanell and Bushee (1997) reduce the number of ratios to nine.
[26] The study constructs a hedge portfolio that sells low book-to-market firms with low FSCORES and buys high book-to-market firms with high FSCORES.

Thus, leverage ratios could be a potential source of distortion for the GSCORE measure. By contrast, financial leverage is also a common proxy for financial distress.

The following discussed studies within the unstructured approach category use similar ratios with comparable distributions along the PMC classification as the preceding studies. I will therefore forego detailed analyses for the following studies that are also classified into the unstructured profitability forecasting approaches. Beneish et al. (2001) use a two-stage approach for the prediction of extreme stock returns. First, they examine twelve market-based signals to classify stocks among firm characteristics (e.g. firm-size, age, analysts following etc.) and trading characteristics (e.g. daily stock turnover or buy-and hold returns over the last 6 month). This systematic framework provides a descriptive profile of extreme market performers. In the second stage, the authors apply selected accounting ratios to separate 'winners' and 'losers'. Beneish et al. (2001) show that extreme performers share many related market characteristics, and that the incremental forecasting power of accounting ratios with respect to future returns increases after controlling for these attributes.

Chung and Kim (2001) first empirically extract 22 and 26 ratios from an extensive set of 68 financial statement ratios[27] to predict firms' intrinsic value. Calculating the difference between the estimated intrinsic value and actual market price (called 'D-Value'), they evaluate whether a firm is under or overpriced. In order to implement a trading heuristic, Chung and Kim (2001) form hedge portfolios by sorting firms among the D-Values buying (selling) undervalued (overvalued) stocks. Depending on how aggressively hedge portfolios are formed, the authors report abnormal stock returns.

In addition, other papers explore the usefulness of *unstructured profitability forecasting approaches* for markets outside the U.S.[28] Setiono and Strong (1998) transfer the O-P framework to the U.K. market. Like Ou and Penman (1989), the paper shows that investors could gain abnormal returns by predicting one year-ahead earnings changes. However, the strategy does not yield abnormal returns for the U.S. market as reported by Holthausen and Larcker (1992). Skogsvik (2008) establishes a comprehensive prediction model that incorporates an assortment of accounting ratios on the basis of previous studies (Gombola and Ketz 1989b; Ou and Penman 1989; Ou

[27] By transforming Tobin's q into a modified discounted cash-flow model, the authors theoretically show that one should use accounting descriptors out of three PMC categories which proxy firms' ability to generate cash flows, growth in cash flows and assets, as well as risk.

[28] Inter alia, studies back up the need to transfer established findings on other markets because of differences that could emerge due to other local GAAP standards, differences in ownership structures, or country-specific economy and market developments.

1990; Lev and Thiagarajan 1993) for testing the efficiency of the Swedish stock market. His model covers all seven PMC categories. The study investigates both the forecast accuracy of the change in the book returns of owners' equity (ROE) and the out-of sample return prediction for portfolios that are formed with a probabilistic score similar to the O-P framework. The results imply that a univariate prediction model possesses superior forecast accuracy for firms' ROE than the financial statement approach. The same holds for predicting abnormal returns out-of-sample: the univariate model beats the corresponding model that is enriched with accounting ratios. In spite of the higher accuracy of the parsimonious univariate model, abnormal returns from the accounting ratio model are decisively above the Swedish stock market average (12.5%) and similar to the results reported by Holthausen and Larcker (1992).

Comparable to studies from Setiono and Strong (1992) and Skogsvik (2008), there is an increasing body of literature that focuses on cross-country settings. The majority of these studies either uses small sets of accounting descriptors or replicates previous studies. Seng and Hancock (2012) replicate parts of Abarbanell and Bushee's (1997) findings for 33 countries. They document that the model could predict earnings changes in both the short and long term. In contrast to the original study, they find some ratios to be not unconditionally value-relevant. The results rather show that some ratios are influenced by contextual factors such as different industry sectors, macroeconomic conditions, or country-specific deviations. Martinez (1999) follows the 'guided' procedure similar to Lev and Thiagarajan (1993) for French firms and identifies a set of 28 fundamentals and macroeconomic information. The results suggest that financial statements and macroeconomic data provide information to value security prices. Noma (2010) reinforces the findings of Piotroskis' 'FSCORE' for the Japanese stock market. Cheung et al. (1997) examine the relative and incremental usefulness of bottom-line items and accounting multiples (book-to-price and earnings-to-price ratio) for predicting stock returns for the Hong Kong stock market. Alexakis et al. (2010) concentrate their study on the Greek market. Via principal component analysis, the study tries to extract accounting ratios as uncorrelated as possible for predicting stock returns. The results indicate that the emerging Greek stock market does not fully incorporate accounting information since FSA based portfolio selection yields abnormal returns. Canbas et al. (2002) also use principal component analysis in order to identify value-relevant financial ratios for the Turkish stock market. Finally, Abekah (2005) documents the usefulness of publicly available accounting ratios for the emerging Ghanaian stock exchange.

The overall analysis of studies using an *unstructured profitability forecasting approach* reveals an extreme heterogeneity of forecast models and financial statement-based ratios. Richardson et al. (2010) conclude that the unstructured use of financial statement-based ratios is subject to the criticism of a 'kitchen sink' approach that uses a number of correlated variables to predict future earnings or stock returns. The overflow of information without sufficient accounting theory leads to concerns of an in-sample identification of variables that might have predictive characteristics. Another concern arises through inconsistent definitions of ratios. Ratios are not only calculated by varying definitions of input variables (e.g. income before or after tax) but also by different scaling.[29] This might increase multicollinearity in regression based forecasting models. The reuse of similar positions as input variables highlights the absence of in-depth analyses of value drivers. Instead of linking a diversified set of non-redundant positions into a comprehensive forecast, similar information gets recycled by a repetitive selection of ratios based on equal financial statement items. Thereby, items from the balance sheet and income statement are of primary interest, whereas items from the cash flow statement are rather of secondary interest. Furthermore, studies forecast the relative change of earnings or stock returns more often than their absolute value. However, little research is available on the benefits and drawbacks of using relative or absolute values. Finally, the literature reports that mutual fund managers hardly outperform the market on average by employing more sophisticated investment strategies in comparison to simple FSA investment strategies (see e.g. Guay 2000) which leaves skepticism towards the implementation of those strategies in a real investment setting. Table 2 gives an overview of the discussed studies of this category.

[29] Sales ratios, for instance, are used in forecasts as absolute level, scaled by firm or market size, or calculated over different time horizons.

TABLE 2

Breakdown of PMC categories into accounting ratios used in unstructured profitability forecasting approaches

Object of Forecast	*Expected Future Earnings*		*Expected Future Returns*	
Metric	*Level*	*Change*	*Level*	*Change*
Effect sign	+ / -	+ / -	+ / -	+ / -
Ratios used				
Return on Investment				
Return on Equity	(-) Ou/Penman (1989); Ou (1990); Skogsvik (2008); Setiono/Strong (1998)	(+) Ou/Penman (1989); Ou (1990)	(+) Chung/Kim (2001); Alexakis et al. (2010)	(+) Chung/Kim (2001)
Return on Assets	(-) Ou/Penman (1989)	(-) Skogsvik (2008)	(+) Setiono/Strong (1998); Alexakis et al. (2010); Mohanram (2005)	(+) Piotroski (2010); Piotroski/So (2012); Noma (2010)
Op. Income / Tot Assets			(+) Chung/Kim (2001)	
Operating Cash Flow > Net income			(+) Mohanram (2005)	(+) Noma (2010)
Loss in previous year			(-) Beneish et al.(2001)	
Growth Income				
Profit Margin	(-) Setiono/Strong (1998)		(+) Alexakis et al. (2010) (-) Chung/Kim (2001)	(+) Piotroski (2000); Piotroski/So (2012); Noma (2010); Beneish et al. (2001)
Gross Margin Ratio	(+) Ou/Penman (1989)	(+) Abarbanell/Bushee (1997) (-) Swanson et al. (2003)	(-) Al-Debie/Walker (1999)	(+) Lev/Thiagarajan (1993); Abarbanell/Bushee (1998); Dowen (2001)
Capital Intensiveness				
Sales			(+) Beneish et al.(2001)	(+) Beneish et al.(2001); Chung/Kim (2001); Mohanram (2005)
Sales / Total Assets		(+) Ou/Penman (1989); Ou (1990)	(+) Setiono/Strong (1998); Alexakis et al. (2010)	(+) Setiono/Strong (1998)
Equity / Assets			(+) Setiono/Strong (1998)	(+) Setiono/Strong (1998)
SG&A Ratio		(-) Lev/Thiagarajan (1993); Abarbanell/Bushee (1997); Swanson et al. (2003)	(-) Al-Debie/Walker (1999)	(+/-) Down (2001) (-) Abarbanell/Bushee (1998)
Depreciation		(-) Ou/Penman (1989); Ou (1990)		(-) Setiono/Strong (1998)
Depreciation / Asstes	(+) Ou/Penman (1989)		(-) Setiono/Strong (1998)	
CAPEX		(-) Lev/Thiagarajan (1993); Ou/Penman (1989); Abarbanell/Bushee (1997); Ou (1990) (+) Seng/Hancock (2012)	(+) Chung/Kim (2001) (-) Al-Debie/Walker (1999)	(-) Abarbanell/Bushee (1998); Beneish et al.(2001); Dowen (2001)
Inventory Intensiveness				
Inventory Turnover	(-) Skogsvik (2008)	(+) Ou/Penman (1989); Setiono/Strong(1998);		(+) Piotroski (2000); Piotroski/So (2012)
Level of Inventories		(-) Lev/Thiagarajan (1993); Abarbanell/Bushee (1997) Stober (1993); Seng/Hancock (2012)		(-) Abarbanell/Bushee (1998); Setiono/Strong (1988); Dowen (2001)
Inventroy/Assets	(-) Ou/Penman (1989); Skogsvik (2008);	(-) Ou/Penman (1989); Ou (1990); Skogsvik (2008);	(+) Chung/Kim (2001)	

Financial Leverage				
Debt / Equity	(-) Ou/Penman (1989)	(+) Ou/Penman (1989)	(-) Alexakis et al. (2010)	
Growth (interes bearing)Debt		(-) Skogsvik (2008)		
Cash flow / Debt	(+) Ou/Penman (1989)			
Level Longterm Debt	(+) Setiono/Strong (1998)		(+) Setiono/Strong (2000); Chung/Kim (2001)	(-) Piotroski (2000); Piotroski/So (2012)
Receivables Intensiveness				
Accounts Receivable	(+) Skogsvik (2008)	(-) Lev/Thiagarajan (1993); Skogsvik (2008); Stober (1993) (+) Abarbanell/Bushee (1997)		(-) Abarbanell/Bushee (1998); Dowen (2001)
Short-term Liquidity				
Current Ratio	(+) Setiono/Strong (1998)	(+) Setiono/Strong (2008); Skogsvik (2008) (-) Ou/Penman (1989)	(+) Alexakis et al. (2010) (-) Setiono/Strong (2000)	
Quick Ratio		(+) Ou/Penman (1989) (-) Skogsvik (2008)		
Cash Position				
Sales/Cash	(+) Setiono/Strong (1998) (-) Ou/Penman (1989)			
Miscellaneous				
Labor Force		(-) Lev/Thiagarajan (1993); Abarbanell/Bushee (1997) Seng/Hancock (2012)	(-) Al-Debie/Walker (1999)	(-) Abarbanell/Bushee (1998); Down (2001)
Order Backlog		(+) Lev/Thiagarajan (1993)		
FIFO (in contrast to LIFO)	(-) Lev/Thiagarajan (1993); Abarbanell/Bushee (1997)		(-) Abarbanell/Bushee (1998)	
Audit Qualification	(+) Abarbanell/Bushee (1997) (-) Lev/Thiagarajan (1993);			(-) Abarbanell/Bushee (1999) (+) Down (2001)
Accruals			(-) Noma (2010)	(-) Piotroski (2000); Piotroski/So (2012)

Notes:

This table breaks down each PMC category into the respective accounting ratios used in the analyzed literature. I further distinguish whether a ratio is used to forecast the change/level of future earnings or the change/level of future returns. (+)/(-) means that a ratio is found to be positively/negatively associated with either future earnings or stock returns. For a detailed definition of each accounting ratio, I refer to the respective study.

2.3 Structured Profitability Forecasting Approaches

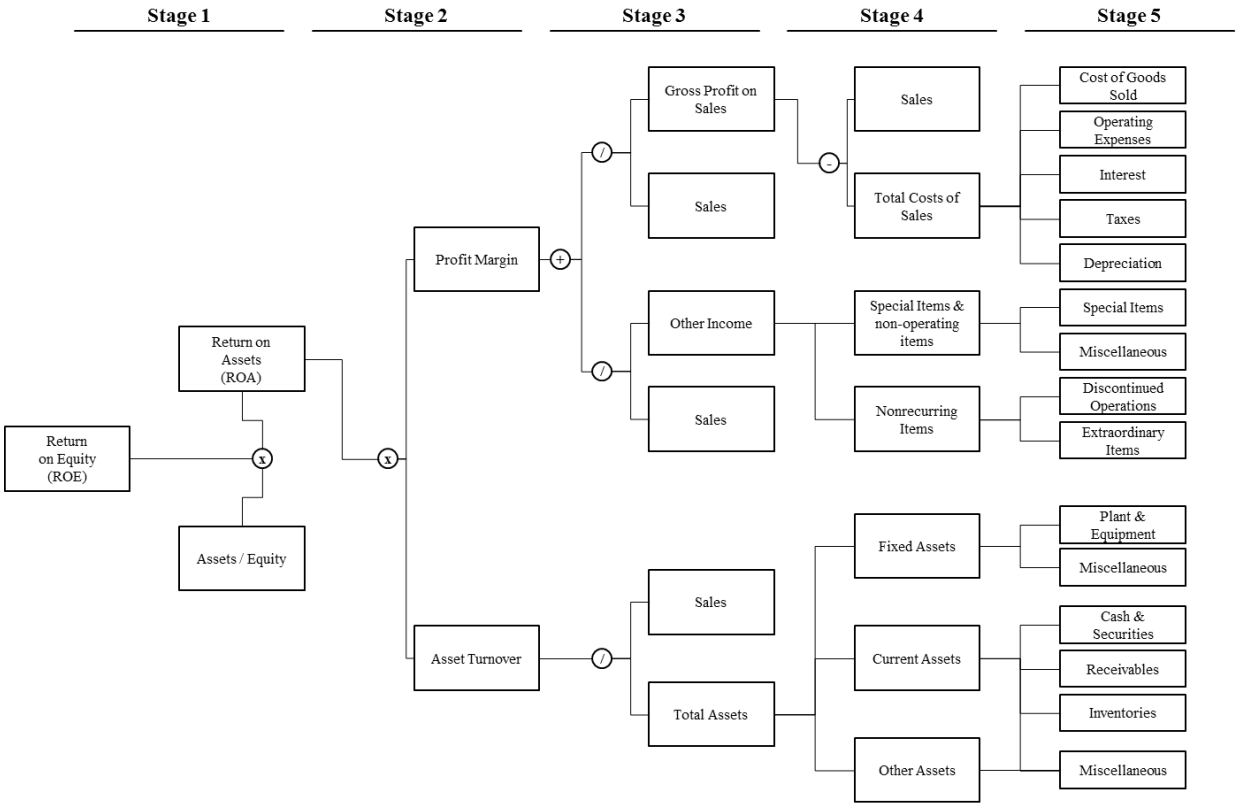
In studies using a *structured profitability forecasting approach*, bottom-line ratios get further decomposed into their single components. Thereby, this stream of literature can generally be divided into two different approaches to structure financial statement-based ratios: the first uses traditional DuPont analysis to comprehensively break down return on assets (ROA) into its single components, examining whether a further disaggregation of ROA components provides more explanatory power to predict future profitability (see Figure 1). The second approach examines a specific segment of a structured disaggregation model of accounting ratios (e.g. profit margin and its single components).

Nissim and Penman (2001) is one of the first studies that examines DuPont analysis to forecast profitability. By analyzing RNOA and its lower order components (asset turnover/ATO and profit margin/PM) [30] in cross-sectional and time series analyses, they show differences in the persistence of each DuPont component. Accordingly, a vast stream of literature comprehensively evaluates the ability of DuPont components in forecasting models. By analyzing different DuPont components, they test whether and to what extent certain disaggregated accounting ratios provide incremental information for estimating firms' future profitability and stock market returns.

[30] ATO measures the efficiency how assets (fixed and current) are managed and used to generate sales. PM measures the firm's ability to control the costs incurred to generate the revenues and reflects the pricing power relative to the market. By analyzing both components in context, one can draw a picture on firms' business strategy.

FIGURE 1

Structure of the DuPont decomposition



Notes:
This figure shows the disaggregation of profitability (defined as ROE and ROA) into its single components along the DuPont decomposition. The decomposition is divided into five stages. Each stage further disaggregates drivers of profitability into subordinated components.

Table 3 gives an overview which ratios were found to be useful for forecasting along the DuPont decomposition. For this purpose, I sort studies by decomposition stages. Most frequently, studies use components from Stage 1 and Stage 2 in their forecasts (ROA/RNOA, ROE, ATO, or PM). Stage 3-4 components are less often examined in the literature. Thereby, studies use both the absolute value and the relative change of accounting ratios. Although absolute and change variables are equally represented in *structured profitability forecasting approaches*, findings suggest that only the change of disaggregated accounting ratios add incremental information to forecasts. For instance, studies show that only the change in ATO is useful for predicting future RNOA whereas the level of ATO does not seem to provide useful information.

TABLE 3

Overview of DuPont components in structured profitability forecasting approaches

Object of Forecast	*Study (Object of Forecast)*		*Object of Forecast*	*Study (Object of Forecast)*	
Metric Effect sign	***Level*** + / -	***Change*** + / -		***Level*** + / -	***Change*** + / -
Level of Stage					
Stage 1			*Stage 2*		
Retruns on (operating) Assets	(-) Soliman (2008)* (Future RNOA) (-) Fairfield / Yohn (2001)* (Future RNOA) (-) Wahlen / Wieland (2011)** (Future Abnormal Returns) (+) Soliman (2008) (Future Abnormal Returns) (+) Fairfield / Yohn (2001)* (Change in operating Income)	(-) Soliman (2008)* (Future RNOA) (+) Fairfield / Yohn (2001)* (Future RNOA) (+) Amir et al. (2011) (Future Abnormal Returns) (+/-) Soliman (2008) (Future Abnormal Returns) (+) Fairfield / Yohn (2001)* (Change in operating Income) (+) Fairfield/Kitiching/Tang (2009) (Future Profit Margin)	*Profit Margin*	(+) Soliman (2008) (Future RNOA) (-) Fairfield / Yohn (2001) (Future RNOA) (+) Soliman (2008) (Future Abnormal Returns) (+) Fairfield/Kitiching/Tang (2009)* (Future Profit Margin) (+) Fairfield / Yohn (2001) (Change in operating Income)	(+) Soliman (2008) (Future RNOA) (+) Fairfield / Yohn (2001) (Future RNOA) (-) Amir et al. (2011) (Future Abnormal Returns) (+) Soliman (2008) (Future Abnormal Returns) (+) Fairfield / Yohn (2001) (Change in operating Income)
Return on Equity	(+) Fairfield/Sweeney/Yohn (1996)* (Future Return on Equity)		*Asset Turnover*	(+/-) Soliman (2008) (Future RNOA) (+) Fairfield / Yohn (2001) (Future RNOA) (+) Soliman (2008) (Future Abnormal Returns) (+) Fairfield / Yohn (2001)* (Change in operating Income)	(+) Soliman (2008)* (Future RNOA) (+) Fairfield / Yohn (2001)* (Future RNOA) (+) Amir et al. (2011)* (Future Abnormal Returns) (+) Wahlen / Wieland (2011)* (Future Abnormal Returns) (+) Soliman (2008)* (Future Abnormal Returns) (+) Fairfield / Yohn (2001)* (Change in operating Income)
Stage 3			*Stage 4*		
Total (operating) Assets		(-) Soliman (2008)* (Future RNOA) (-) Fairfield / Yohn (2001)* (Future RNOA) (-) Wahlen / Wieland (2011)* (Future Abnormal Returns) (+) Fairfield / Yohn (2001)* (Change in operating Income)	*Fixed Assets*		(-) Soliman (2008)* (Future RNOA) (-) Soliman (2008)* (Future Abnormal Returns) (+) Amir et al. (2011)* (Future Abnormal Returns)
Sales		(+) Wahlen / Wieland (2011)** (Future Abnormal Returns)	*Current Assets*		(-) Soliman (2008)* (Future RNOA) (-) Soliman (2008)* (Future Abnormal Returns) (+) Amir et al. (2011)* (Future Abnormal Returns)
Other Items	(+) Lipe (1986)* (Future Abnormal Returns)		*Other Profit Margin*		(+) Amir et al. (2011) (Future Abnormal Returns)
Gross Profit Margin	(+) Lipe (1986)* (Future Abnormal Returns) (+) Fairfield/Sweeney/Yohn (1996) (Future Return on Equity)	(-) Amir et al. (2011) (Future Abnormal Returns) (+) Wahlen / Wieland (2011)* (Future Abnormal Returns)	*Special & Non-operating Items*	(-) Fairfield/Kitiching/Tang (2009)* (Future Profit Margin) (+) Fairfield/Sweeney/Yohn (1996)* (Future Return on Equity)	
			Nonrecurring Items	(+) Fairfield/Sweeney/Yohn (1996)* (Future Return on Equity)	

Stage 5			*Stage 5*	*Continuation*	
SG&A	(+) Fairfield/Sweeney/Yohn (1996) (Future Return on Equity)	(-) Wahlen / Wieland (2011)* (Future Abnormal Returns) (-) Lipe (1986)* (Future Abnormal Returns)	*Receivables*		(+/-) Stober (1993)* (Future Sales) (-) Stober (1993)* (Future Profit Margin) (-) Stober (1993)* (Future Earnings)
Depreciation	(+) Fairfield/Sweeney/Yohn (1996) (Future Return on Equity)	(-) Lipe (1986)* (Future Abnormal Returns)	*R&D*		(+) Sougiannis (1994)* (Future Earnings) (+) Chan/Lakonishok/Sougiannis (2001) (Fut.Abnormal Returns)
Interest	(+) Fairfield/Sweeney/Yohn (1996) (Future Return on Equity)	(-) Lipe (1986)* (Future Abnormal Returns)	*Inventories*		(+/-) Bernard / Noel (1991)* (Future Sales) (-) Bernard / Noel (1991)* (Future Earnings)
Tax	(+) Fairfield/Sweeney/Yohn (1996) (Future Return on Equity)	(-) Lipe (1986)* (Future Abnormal Returns)	*Discontinous / Operaing Items*	(+) Fairfield/Sweeney/Yohn (1996) (Future Return on Equity)	

Notes:
This table breaks down each stage of the DuPont decomposition into the respective accounting ratios used in the analyzed literature. I further distinguish whether a ratio is used to forecast the change/level of the forecasting objective. The respective forecast objective is indicated in brackets behind the analyzed study. (+)/(-) means that a ratio is found to be positively/negatively associated with the forecast objective. For a detailed definition of each accounting ratio, I refer to the respective study. * indicates that a variable was found to have statistically significant information content to predict the respective forecast objective.

Stage 1 starts with the structured disaggregation of accounting ratios along the DuPont analysis. Instead of using ROE, most studies focus on RNOA since operating assets do not include financing decisions (e.g. Fairfield and Yohn 2001; Soliman 2008; Fairfield et al. 2009; Amir et al. 2011). Thereby, studies investigate different specifications of ROA/RNOA. For example, they test if the absolute value or the change in RNOA reverts to an industry/market mean[31] and whether this mean reversion effect impacts forecasts (e.g. Freeman et al. 1982). However, findings indicate that ROA/RNOA is only incrementally useful in predicting future profitability but not stock returns. The majority of surveyed studies therefore concludes that a further disaggregation of this bottom-line profitability ratio could enhance forecasts' accuracy.

Fairfield and Yohn (2001) test whether disaggregating RNOA into ATO and PM (Stage 2) increases the out-of-sample predictability compared to a forecast that just uses Stage 1 variables. They show that only the change in both components provides additional explanation for one year-ahead RNOA whereas the absolute level is not found to be incrementally useful. Furthermore, the authors show that ATO in particular possesses more explanatory power than PM. This effect is extensively confirmed by subsequent research (e.g. Soliman 2008; Demmer 2015). However, markets seem to ambiguously react towards both components. Over a longer time horizon up to three years after the release of financial statements, studies find a positive association

[31] Mean-reverting tendencies can also be observed by looking at the expected effect sign: the absolute level is predominantly negative correlated with ROA/RNOA as well as abnormal stock returns.

between future abnormal returns and changes in ATO whereas an association for PM cannot be documented (Soliman 2008; Amir et al. 2011). Immediately after earnings announcements, however, markets' reaction towards unexpected changes in PM is larger than towards changes in ATO. At the first glance, these findings might seem inconsistent but they do comply with the prevailing opinion that investors react stronger towards earnings rather than revenue surprises around actual announcements (e.g. Jegadeesh and Livnant 2006; Kama 2009).

Along with studies attributing ATO a higher persistence than PM that is said to embody more transitory monopoly returns (e.g. Romer 1986), market reactions do not seem to properly impound the stable character of ATO over long-time horizons and, simultaneously, overreact naively towards changes in faster diminishing profit margins. This myopic market response to ATO and PM emphasizes the advantage to further disaggregate performance indicators as applied in unstructured FSA approaches. It also helps to understand what finally drives ROA/RNOA. Firms either try to increase profitability through high return-yielding, more transitory competitive advantages or through the effective usage of assets. This separation not only reveals business strategies but also draws inferences on the expected persistence of profitability. Consequently, analysts could more precisely analyze the common persistence of RNOA by including the conditional persistence of ATO and PM for explaining RNOA. By using the aggregated form of ROA/RNOA only, incrementally useful information might get lost.

Stage 3 focuses on understanding firms' business models in more detail. The sales-to-assets relation reflects not only companies' asset management but also other characteristics such as capital intensiveness (e.g. firm size expressed by the amount of total assets), growth opportunities (e.g. yearly growth rate in sales), or core earnings (e.g. differentiation between net income and other income). However, little research is available on the usefulness of Stage 3 ratios in forecasting models. With the exception of changes in total assets which are negatively associated with future firm and stock market profitability (e.g. Soliman 2008; Fairfield and Yohn 2001; Wahlen and Wieland 2011), other components are only sparely investigated. Therefore, more research is needed in order to better understand the impact of the immediate drivers of PM and ATO. Especially, it might be of interest to classify different firm profiles along Stage 3 characteristics in order to forecast ATO, PM, RNOA, and stock market returns more precisely (e.g. incorporate factors as e.g. industry membership, size or risk).

Literature devotes more effort in analyzing Stage 4 components where drivers of ATO and PM get decomposed in greater detail than in Stage 3. Total assets are decomposed into fixed, current and other assets to investigate their different properties and persistence. Both, changes in fixed assets and changes in current assets are assumed to be incrementally value relevant. Work by Amir et al. (2011) applies DuPont analysis for Stage 1-4 components in order to explain the persistence of a component higher in the structural hierarchy (e.g. Stage 2) with the persistence of its components one hierarchy level below (e.g. Stage 3). Therefore, profitability forecasts do not rely on autocorrelation coefficients of certain components but are conditionally related to their lower order drivers. Amir et al. (2011) empirically demonstrate that markets react stronger to changes in fixed assets rather than to changes in working capital. The positive correlation of changes in current/fixed assets and future abnormal returns reflects markets' favor for substantial growth (Fama and French 1998). Against this, Soliman (2008) finds changes in fixed and current assets to be negatively associated with future profitability. The paper primarily investigates the usefulness of a second-order decomposition (Stage 2: PM and ATO) for FSA forecasts. To this extent, the paper also includes current and fixed assets to control for the influence of total accruals since they were also found to be value-relevant to predict future earnings (e.g. Richardson et al. 2005). Consistent with the accrual anomaly literature, higher accruals and growth have equivalently negative associations with one year-ahead return on assets (Fairfield et al. 2003). Fairfield et al. (2009) further disaggregate the PM branch in Stage 3-4 components. They find that the association between special items and future profit margin differs significantly between firms with low and high degrees of profitability. Especially for high profit firms, negative special items correlate with lower future profit margins. Up to this point in time, there is no study that merges the latest insides of decomposing PM and ATO branches beyond Stage 2 in a joint model.

In summary, I note that studies with *structured profitability forecasting approaches* mitigate one of the major concerns of *unstructured* forecast models. This is that these forecasts are set up by a structural relation with less redundant information and with more comprehensive coverage of accounting ratios. One might ascribe this progress to the common criticism in the late 1990s that FSA forecasts are guided without much structure and theory. I see the most important contribution of this literature stream in the finding that not the quantity of used ratios improves forecasts accuracy but rather the careful selection and composition of accounting ratios. To this extent, forecasting models do not have to add more granularity with more decomposed accounting ratios to shed light on the finest drivers of firms' profitability. It is more a

matter of theory what is most value-relevant for predicting future firm and stock market performance as well as a matter of econometrical feasibility to make predictions for uncertain future points in time.

2.4 Theory-Driven Profitability Forecasting Approaches

The studies which I refer to as *theory-driven profitability forecasting approaches* incorporate financial statement-based ratios and other information on the basis of economic theory and institutional knowledge taken from latest accounting research findings. These studies therefore neither incorporate a large set of accounting ratios nor follow a fixed structural relation such as the DuPont disaggregation. To provide a thorough overview of these type of studies, I further divide the *theory-driven profitability forecasting approaches* literature into five clusters: the first cluster exploits the differential usefulness of *operating and financial activities* for predicting future profitability. The second cluster includes studies which analyze the time-series behavior of earnings and its components arising from the *accruals anomaly*[32]. Third, a*ccounting conservatism* directs the focus on biases in the accounting system arising from the asymmetric recognition of value relevant events. In addition, the interaction between conservatism and other factors such as growth and/or earnings persistence is examined. The fourth cluster includes studies which analyze different *definitions of earnings components*. In the limelight of this field, studies formulate various definitions of earnings by either adding or stripping off information from bottom-line earnings. Thereby, studies bear upon research on how capital markets perceive information from different earnings components and whether knowledge on such market behavior helps predicting future excess returns. The fifth cluster includes studies which adopt techniques from the *firm valuation literature*.

Table 4 presents an overview of the five clusters with details on the main focus, the forecast objective, and the object(s) of investigation of the most relevant studies using *theory-driven profitability forecasting approaches*.

[32] The accruals anomaly is usually defined as the negative relationship between accounting accruals and subsequent stock returns. See Richardson et al. (2010) for a detailed introduction into the accruals anomaly literature.

TABLE 4

Overview on theory-driven profitability forecasting approaches

Category of approach	*Main Focus*	*Studies*	*Forecast Objective*	*Explanatory Variables / Object of Investigation (+ / -)*
Distinguishing Operating and Financing Activities	Differentiation between leverage that stems from either financing or operating activities	Nissim / Penman (2003)	Future ROCE	(+) Operating Leverage*
			Future P/B ratio	(+) Operating Leverage*
	Disaggregation of accounting profitability into operating and financing activities	Lim (2013)	Current Market-to-book ratio	Operating > Financing activities
	Disaggregation of accounting profitability into operating and financing activities	Esplin / Hewitt / Plumlee / Yohn (2013	Future ROE	Operating > Financing activities
Accruals Anomaly	Markets" awareness of processing the information of accruals and cash flow components contained in current earnings	Sloan (1996)	Persistence of Earnings	(-) Accruals*
			Future Stock Returns	(-) Accruals relative to cash flow components
	Confirming that Sloan's accrual anomaly holds also for firms with more sophisticated (e.g. institutional) investors	Ali / Hwang / Trombley (2000)	Future Stock Returns	(-) Accruals relative to cash flow components
	Testing whether markets' mispricing of accruals arises in discretionary accruals rather than just "normal" accruals	Xie (2001)	Future Earnings	(-) Discretionary accruals*
			Future Stock Returns	(-) Discretionary accruals*
	Extension of Sloan (1996). They show that markets do not seem to understand the least reliable accruals which is likely to be influenced by opportunistically managerial behavior	Richardson / Sloan / Tuna (2005)	Future ROA	(-) Accruals and its decomposed components
			Future Stock Returns	(+/-) Accruals and its decomposed components**
Accounting Conservatism	Study builds scoring model that should capture the joint effect of conservative accounting and growth through investments. The authors use the scoring model to predict future RNOA as well as future returns on the stock market	Penman / Zhang (2002)	Future RNOA	(-) Conservative Acc.* (-) Growth in Investments*
			Future Stock Returns	(-) Earnings Quality affected by conservatism
	The study uses several different measures to provide evidence on the increase of conservatism by U.S. firms. They also link the historical examination to FSA in order to show the benefits of incorporating conservatism in prediction models	Givoly / Hayn (2002)	Persistence of economic performance of companies over time	(-) Conservatism as: Negative n-o accruals Timeliness news Skewness and variability of earnings Change in M/B ratio
	The paper analyze two influencing variations in B/M ratio: Biases (constant distortion of B/M value due unconditional conservatism) and lags (asymmetrical realization of gains and losses; conditional conservatism)	Beaver / Ryan (2000)	Future ROE	(-) Conditional Conservatism (-) Unconditional Conserv.
	Reexamination of conservatism as measured by previous studies and the influence on firms' value relevance	Balachandran / Mohanram (2011)	Value Relevance by - Stock price - Stock returns Perfect foresight	(+/-) Conservatism as defined by - Penman/Zhang (2002) - Beaver/Ryan (2000)

Definitions of Earnings and Capital Market Reactions	Examination whether Pro Forma Earnings (exclusion of certain expenses such as non-recurring or non-cash items). The study concludes that those excluded items are incremental relevant for FSA	Doyle / Lundholm / Soliman (2003)	Future Cash Flows	(-) Pro Forma Earnings *
			Future Stock Returns	(-) Pro Forma Earnings *
	Empirical analysis whether the inclusion of historical earnings volatility helps in predicting future earnings. The results indicate the usefulness of examines earnings volatility	Dichev / Tang (2009)	Future Earnings	(-) Earnings Volatility*
	Investigation whether in- or excluding special items form "street" earnings provides information useful for FSA prediction stock returns and earnings	Hsu / Kross (2012)	Future Earnings	(-) Special Items*
			Future Stock Returns	(-) Special Items*
Forecasting and Firm Valuation	Implementing a two-step strategy to yield abnormal stock returns: first, a autoregressive model should predict changes in future ROE. Second, they compare market valuation against a residual income valuation, spotting where mispricing likely occurs	Skogsvik / Skogsvik (2010)	Future Stock Returns	(+) Prediction of ROE* (-) ROE market vs. RI model*
	Study calculates firms' RI value based on analysts' forecast in order to predict future stock market returns	Frankel / Lee (1998)	Future Stock Returns	(+) RI-Value/Price ratio*
	Confirmation of Frankel/Lee (1998) with additional controls for several risk proxies	Ali / Hwang / Trombley (2003)	Future Stock Returns	(+) RI-Value/Price ratio*
	Investigation whether cash profitability enhances prediction of future earnings and whether markets fully comprehend the characteristics of this profitability indication	Hirshleifer / Hou / Teoh / Zhang (2004)	Future Earnings	(-) Net operating assets (NOA)*
			Future Stock Returns	(-) Net operating assets (NOA)*

Notes:
This table gives an overview of studies that are clustered within the section of theory-driven profitability forecasting approaches. In addition, the table also shows the respective forecast objective as well as the main forecast variables of the forecasting model. (+)/(-) means that a ratio is found to be positively / negatively associated with the forecast objective. For a detailed definition of each accounting ratio, I refer to the respective study. * indicates that a variable was found to have statistically significant information content to predict the objective of the forecast.

Cluster I: Distinguishing between operating and financial activities

The main focus of studies within this cluster concerns the question whether separating financial activities and operating activities results in more accurate forecasting models. Following the seminal work from Feltham and Ohlson (1995) and Modigliani and Miller (1958), studies primarily incorporate information on firms' operating activities into forecasts since financial activities are assumed to have zero net present value.[33] Consequently, financing activities are regarded as uninformative for predicting future profitability and are thus excluded from forecasts. In the same line, financial assets and liabilities are reported close to the market value and are, therefore, not relevant for firm valuation and forecasting. Nissim and Penman (2003) expand traditional DuPont disaggregation by further differentiating between two leveraging equations for explaining cross-sectional differences in current and future rates of return as well as price-to-book ratios. The first leveraging equation stems from financing

[33] Financial assets and financial liabilities are under typical circumstances close to market value in the balance sheet. This implicates that these positions are already valued properly.

activities such as raising funds from the capital market. The second leverage equation emerges from business activities where firms' interact with suppliers, employees, and customers. Nissim and Penman (2003) show that effects from financing activities on current and future rates of return as well as price-to-book-ratios are less persistent than those from operating activities.

Standard setters and other financial statement users discuss whether separating financing and operating activities might be anchored into regulatory frameworks to improve firm valuation and forecasting. The International Accounting Standards Board (IASB 2010) as well as the Financial Accounting Standards Board (FASB 2010) released exposure drafts requiring firms to disaggregate their financial statements using the operating and financial distinction.[34] Although the effect of a disaggregation is widely assumed to be relevant and emphasized in the accounting valuation and forecasting literature, there is little empirical evidence that this separation increases the accuracy of FSA models. Lim (2014) extends the findings of Nissim and Penman (2003) by showing that profitability arising from operating activities is more strongly associated with stock market returns than profitability from financing activities. In addition, Lim (2014) also provides empirical evidence that the usefulness of disaggregation originates from different levels of persistence of accounting profitability components (conditional versus unconditional as distinguished in Amir et al. 2011).[35] Therefore, the study attributes both the distinction between financial and operating activities as well as the structured decomposition of accounting profitability in accordance with DuPont analysis to possess incremental usefulness for FSA models. Against this, Esplin et al. (2014) find the disaggregation to be only informative for predicting future profitability. The authors compare out-of-sample forecasts based on disaggregated financial and operating activities against a prediction model that stripes unusual and infrequent items away from bottom-line earnings. The disaggregation thereby produces less accurate forecasts. Nevertheless, they find that the combination of the operating/financial with the unusual/infrequent disaggregation improves forecasts compared to a simple disaggregation. As a result of these inconsistent and sparse findings on the benefits of treating financial and operating actives differently in FSA forecasts, we cannot rule out whether this accounting theory driven approach helps improving forecasts models by its own, without further partitioning items with different persistence (e.g. unusual/infrequent items as e.g. Esplin et al. 2014). Furthermore,

[34] By the time publishing this review, such proposal was still discussed and under review from FASB and IASB.

[35] Amir et al. 2011 define the conditional persistence as the marginal contribution of a decomposed component's persistence to the persistence of an aggregated profitability. The unconditional persistence is defined as the autocorrelation coefficient from an accounting ratio's time-series.

valuation literature gives evidence that the aggregated Ohlson (1995) model predicts one year-ahead prices more precisely than the disaggregated Feltham and Ohlson (1995) model (Callen and Segal 2005).

Cluster II: The accruals anomaly in forecasts:

Total accruals can be classified into discretionary (abnormal) and non-discretionary accruals. In order to determine discretionary accruals, accounting research spent much effort in developing models that estimate the discretionary accruals share as accurately as possible (e.g. the DeAngelo 1986 model; the Jones 1991 model; the modified Jones model by Dechow et al. 1995; the adopted-modified Jones model by Dechow et al. 2003; the performance matched model by Kothari et al. 2005). All of these models assume contracting and political cost based principal-agency-conflicts insofar that managers either attempt to increase their incentives or convey insider information about firm's periodic performance by managing accounting numbers (see Kothari 2001). Thus, discretionary accruals are supposed to explain the degree of opportunistic distortions in financial statements. Researchers make various assumptions where distortions are likely to occur in the financial statements. In turn, each discretionary accruals model alternately reflects accountants' underlying theories of how one can disentangle managements' influence from fundamental performance in firms' financial statements.

FSA literature uses different models that estimate both discretionary and non-discretionary accruals as either sole or additional component in forecast models. Sloan (1996) was one of the first to link the vast accruals anomaly literature with financial forecasting. The study shows how knowledge about earnings persistence can be utilized to predict stock returns. Sloan (1996) hypothesizes that the persistence of current earnings is decreasing (increasing) with high (low) reported accruals. The author follows that capital markets do not appear to comprehend the different transition of accruals and cash flow components and, therefore, overestimate the persistence of accruals and underestimate the persistence of cash flows. Using a simple trading heuristic that buys firms with low levels of accruals relative to cash flows and that sells those with high levels of accruals relative to cash flows, Sloan indicates that the accrued share contained in single financial statements components can yield abnormal returns. The documented unawareness of investors towards accrual accounting triggered the formation of an own field of research that refines the prediction of future earnings, stock returns and risk with the assistance of accrual accounting (e.g. Ali et al. 2000; Xie 2001; Fairfield et al. 2003; Richardson et al. 2005; Mashruwala et al. 2006;

Chan et al. 2001; Khan 2008). Basically, well-known accrual models are modified to investigate the persistence of certain accrual components of accounting income. Most accrual based forecast designs are quite similar among each other. For the sake of brevity, I refer to other reviews which discuss aspects of the accrual anomaly in more depth (e.g. Kothari 2001; Beaver 2002; Richardson et al. 2010; Dechow et al. 2011). However, I note that both types of accruals, discretionary as well as non-discretionary accruals, were found to have predictive power in FSA forecasting models (see Table 4). Over the past ten years, accounting research spent much effort to analyze not only an aggregated estimation for accruals to predict future stock returns and firm profitability but also the predictive power of single accruals components. The latest evidence is mixed. Reexaminations show that stock returns from accruals based trading can be explained by other factors (such as idiosyncratic risk Mashruwala et al. 2006; earnings manipulation Chan et al. 2001). For forecasting profitability, research emphasizes to include components or drivers of accruals to increase the predicate power of the FSA models (e.g. growth components; see Fairfield et al. 2003).

Cluster III: Accounting Conservatism

Although no authority definition has been established that defines conservatism in accounting, conservatism generally embraces the asymmetrical recognition of profits and losses. In particular, conservatism is 'a prudent reaction to uncertainty to try to ensure that uncertainty and risks inherent in business situations are adequately considered (FASB Statement of Concepts No. 2). From the vantage point of FSA, conservatism generally plays a decisive role insofar as it potentially distorts accounting ratios as reported in firms' financial statements. As documented in prior research, analysts are aware of conservatism and try to adjust the influence of conservatism ex post (e.g. French and Poterba 1991). Surveying the FSA literature, I identify two different *theory-driven profitability forecasting approaches* to incorporate conservatism into forecasting models. The first approach uses measures of conservatism to predict future profitability. The second approach sorts firms according by the degree of conservatism contained in financial statements. Afterwards, those studies try to exploit markets' unawareness towards conservative accounting by buying/selling stocks.

Beaver and Ryan (2000) investigate whether distinguishing between predetermined unconditional conservatism and event-driven conditional conservatism

is beneficial for predicting future profitability.[36] They hypothesize and document that their measure of unconditional conservatism has more persistent cross-sectional association with future book return on equity. They also provide evidence that the association between conservative accounting and the predictability of future profitability is influenced by firm growth. This well-known interaction between conservatism and growth (Feltham and Ohlson 1995) is also the research subject in Penman and Zhang (2002). Their approach involves changes in growth under conservative accounting. They hypothesize and show that conservative accounting reduces earnings quality when a firm has material changes in capital expenditures for business operations. By constructing a scoring measure for conservatism and earnings quality, they empirically demonstrate the usefulness of this scoring measure of conservatism and earnings quality for predicting future RNOA and abnormal stock market returns. Similarly, Givoly and Hayn (2002) demonstrate increasing conservatism[37] in financial statements of U.S. companies over the past 50 years that has not fully been incorporated by investors.

Critical remarks in the accounting literature challenge not only the question to what extent conservatism is useful in FSA forecasting models. It is not even common sense if one can actually distinguish between unconditional and conditional conservatism.[38] This has crucial implications for forecasting models since the nature of conditional and unconditional conservatism (unconditional, latent adjustments versus conditional, event specific adjustments) requires different approaches and treatments in forecasting models. Balachandran and Mohanram (2011) reexamine models by Beaver and Ryan (2000) as well as Penman and Zhang (2002) to measure conservatism. They provide empirical evidence that more conservative firms do not exhibit decreasing value relevance for explaining stock prices with earnings and book values. Callen and Segal (2013) claim that all currently applied models of accounting conservatism lack in incorporating appropriate proxies for conditional conservatism. Their finding implies that accounting research still has to elaborate on more reliable methods to quantify conservative accounting and to adjust ratios in FSA forecasts for this effect.

[36] This research extends the well-investigated literature that examines book-to-market ratios in order to predict ROE (e.g. Fama and French 1995; Penman 1992).
[37] There exist several different proxies for conservatism: inter alia, nonoperating accruals, news in reported earnings, variability and skewness of earnings, changes in M/B-ratios.
[38] For instance, papers by Dietrich et al. (2007), Givoly et al. (2007), or Patatoukas and Thomas (2011) offer criticism to the ability of the Basu (1997) equation to distinguish between conditional and unconditional conservatism. Ball et al. (2013) again reinforces the asymmetric earnings timeliness approach of Basu (1997).

Taken together, conservatism is a controversy discussed issue with several unanswered issues. Literature is still trying to frame proper measurements for different types of conservatism. The FSA literature steadily adopts different findings to adjust FSA information for possible distortions from conservative accounting. However, it is not clear if these findings suffer under omitted variable biases or imprecise measurements of conservatism. It is also conceivable that markets might be aware of conservatism in accounting ratios but are willing to pay beyond fair value for having an insurance premium against overoptimistic financial statement ratios.

Cluster IV: Definitions of earnings and capital market reactions

Earnings and earnings components are one of the most analyzed financial figures since they are found to be the key metrics used by investors as well as important factors for determining managerial efforts (Graham et al. 2005). The FSA literature builds on the relevance of these financial statement components to evaluate them in forecasting models. Similar to *structured profitability forecasting approaches*, the theory-driven decomposition of earnings literature follows a mechanical procedure to analyze the forecasting relevance of earnings and earnings components (e.g. Fairfield et al. 1996). However, instead of being guided by fixed structured relations, accounting theory replaces purely systematical approaches. Doyle et al. (2003) draw on studies that examine market's response to different definitions of earnings. In particular, they examine the issue whether pro forma earnings[39] are an indication for firms' current and future value (e.g. Bradshaw and Sloan 2002; Lougee and Marquardt 2004). Doyle et al. (2003) show that the market does not appear to systematically understand firms' pro forma earnings as well as that higher levels of exclusions lead to lower future cash flows. Hsu and Kross (2011) focus on the inclusion/exclusion of special items in pro forma earnings. They find a negative persistence between special items and future earnings as well as a negative relation between future stock returns when special items are included in pro forma earnings. This supports the importance of carefully evaluating components of earnings such as special items in order to consider their opportunistic utilization by firms' management. Dichev and Tang (2009) do not question the impact of certain items on the predictability of forecasts but rather whether earnings volatility matters in general. They document that earnings volatility is negatively correlated with earnings predictability and that an inclusion of earnings volatility proxies raises the accuracy of predicting earnings in the short and long run.

[39] Pro forma earnings exclude certain expenses that are judged to be unimportant to assess firms' fair value, e.g. non-recurring items or special charges.

Commonly mentioned criticism of this cluster is that the majority of studies disproportionally focus on whether earnings components add incremental information to forecasts without regarding the condition that drives certain components. For instance, literature claims that special or extraordinary items are frequently used by management to affect earnings in order to signal positive news to the markets.[40] In unfavorable economic conditions, different earnings components can be used by firms' management to partially compensate for a poor business environment. Hence, it would be beneficial implementing information on disaggregated earnings components either on a case specific basis [41] or in interactions with economic conditions in order to control for situations when these components are likely to possess high explanatory power. Due to the infrequent nature of certain earnings components, forecasts that unconditionally include transitory items could lose forecast power. We therefore emphasize more research that helps to better understand drivers and implications of different earnings components in order to increase forecasts' accuracy.

Cluster V: Forecasting and Firm Valuation

The studies within this cluster build forecasting models in accordance with firm valuation theory (see for an overview on the valuation literature textbooks from e.g. Damodaran 2006 or Kruschwitz and Löffler 2006). Before presenting studies in detail, we want to remark that prediction models from this category imply a high degree of complexity. The valuation literature involves a range of financial statement information. However, it is still controversy discussed whether more complex forecasting models beat predictions from a random-walk or an autoregressive forecast model (see e.g. Welch and Goyal 2008). It is up to the analyst to weigh the trade-offs between more parsimonious models and more detailed models.

Skogsvik and Skogsvik (2010) combine an *unstructured profitability forecasting approach* with the residual income valuation technique. In order to analyze whether such combination can yield abnormal stock market returns, the authors build a simple probabilistic prediction model of changes in firms' ROE. Afterwards, they set these results in contrast to markets' expectations that are extracted from a residual income valuation model. In doing so, they aspire to detect two sources of mispricing:

[40] E.g. earnings smoothing to show a steady growth situation, increasing earnings to meet analysts 'consensus forecast etc.

[41] It would be conceivable, for example, that unusually and infrequently high extraordinary items in the previous year could be driven by goodwill impairment. Goodwill impairments, in turn, could be indicative for a big bath accounting. Hence, this uncommonly high extraordinary item position in the current year is likely to be a singular, non-recurring event. Forecasting models, as a consequence, that just use extraordinary items in a naïve manner could be distorted.

forecasting mispricing and modelling mispricing. The forecasting mispricing is that stock prices do not fully reflect the forecasting ability of published accounting information with respect so some value drivers. The modelling mispricing is that stock prices do not reflect the valuation implications of forecasted value drivers appropriately. The intersection of these two sources of potential mispricing sets up a trading heuristic that takes positions when the ROE prediction and market expectations differ.[42] This investment strategy generates positive excess returns for the Swedish stock market for the early 1990s' up to 1995. After 1995, abnormal returns from this investment strategy diminish. Skogsvik and Skogsvik (2010) conclude that investors continuously gained insights in processing publicly available financial statement information. In contrast to the Swedish stock market, studies confirm the usefulness for using valuation models for predicting future firm performance and abnormal returns for U.S. markets after 1995. Frankel and Lee (1998) use analysts' earnings forecasts for calculating firms' fundamental value in accordance with the residual income valuation model. The authors then analyze the correlation between the estimated firm value and contemporaneous stock prices. The study finds that stock prices gradually converge to the calculated firm value. This would mean that market participants either do not fully process analysts' forecasts or that market participants do not properly incorporate financial statement information. After controlling for various risk proxies and alternative explanations, Ali et al. (2003) confirm the finding of Frankel and Lee (1998).

Furthermore, Hirshleifer et al. (2004) examine different impacts of net operating income against cumulative free cash flow for predicting future earnings as well as future stock returns. Thereby, they claim that investors naively focus on accounting profitability and pay limited attention towards other variables for predicting future performance. According to the authors, cash profitability is a steadily neglected profitability indicator that could serve as an explanatory factor for mispriced stocks. This claim is based on the assumption that investors tend to be overoptimistic towards firms' recent earnings growth but fail to recognize the probability of declines in the following periods due to mean-reversion. Fairfield et al. (2009) further analyze the impact of mean-reversion in firms' profitability for models that either use industry-specific information or economy-wide information. In contrast to the large academic body that suggests systematic industry differences to be relevant for valuation and forecasting, the paper documents that industry information are uninformative for

[42] E.g. Skogsvik and Skogsvik (2010) take a long (short) position when forecasts predict a probability of higher (lower) future ROE compared to historical ROE and when, simultaneously, the market price is undervalued (overvalued) according to the RI valuation model.

predicting future profitability and that they are only incrementally useful for predicting firm growth.

3. The Influence of Persistence, Growth and Conservatism on Profitability Forecasting

3.1 Theoretical Concept and Outline

As highlighted above, the seminal work of Feltham and Ohlson (1995) outlines the relationship between firm value and accounting numbers. In addition, the study highlights three parameters as important factors which influence accounting numbers: earnings persistence, growth in operating assets, and conservative accounting. Leaving aside the fact of how one can operationalize the F-O model by including a firm's expected profitability several years ahead, it is consensus of belief that those three parameters are an important part for accounting based valuation models (see Callen and Segal 2005). The F-O approach uses these three parameters in a linear model that specifies the dynamics of an information set for making assumption about how accounting numbers determine firm value. All three factors are interrelated in a closed form and they influence the relation between market value and accounting data.

In the following chapter, I illustrate how different assumptions about earnings persistence, growth, and conservative accounting bias current profitability ratios. Further, I survey whether and to what extent the FSA literature incorporates influences of these parameters into forecasting models. I start with a fairly simple numerical example that captures the mutual influence of growing assets and conservative accounting. Based on that, I investigate whether and to what extent those factors determine forecasts' accuracy. For that purpose, a Monte Carlo simulation[43] is performed. In doing so, I show the forecast dispersion that could emerge from the interaction between fundamental performance and the configuration of the accounting system.

3.2 Simulation

The numerical example in Table 5 sets the ground for the subsequent Monte Carlo simulation. In particular, the impact of two central variables on a firm's accounting

[43] Monte Carlo simulation uses repeated sampling to determine the properties of some phenomenon (see Sawilowsky et al. 2003). Monte Carlo simulation is often used for optimization problems, numerical integration, or generating draws from a probability distribution.

profitability (expressed as ROA) is presented: accounting conservatism and growth in assets. I consider four cases: first, the numerical example shows the valuation of firm's profitability in a steady-state (no growth) under neutral accounting. Second, I assume a constant growth in firm's operating assets under neutral accounting. Third, I assume a steady-state under conservative accounting. Last, I simultaneously consider both scenarios, growth in assets and conservative accounting.

As a matter of simplicity, I outline the operations of a firm with three factors: the firm uses (i) net operating assets (NOA) to generate (ii) revenues (REV) while it faces (iii) depreciation charges (DEP) for the involved assets. All other costs are assumed to stay constant so that the firm generates equal returns of 10% from revenues each fiscal year. Hence, the difference between revenues and depreciations equals net income (NI). The yearly profitability is thereby measured as the return on operating assets ($ROA_t = NI_t / NOA_{t-1}$) and the firm's residual income ($RI_t = NI_t - NOA_{t-1} * r$), where r is the expected return rate of 10%.

To make Cases I – Case IV comparable, I assume the same amount of assets and revenues for each case in the initial period. Only the growth rate in assets and the degree to which the firm practices conservative accounting varies.

Case I assumes a steady level of operating assets and no practice of conservative accounting choices for determining depreciation rates. Under these circumstances, the firm produces a constant stream of net income and profitability.

Case II assumes a yearly linear growth in assets. In unsaturated markets, these increasing assets produce more revenues. However, higher operating assets generate higher depreciations. Accordingly, firms accounting profitability remains the same as in Case I.

Case III introduces the use of conservative accounting choices. Following the literature (e.g. Beaver and Ryan 2000; Rajan et al. 2007), I model conservatism through accelerated depreciation charges. Instead of writing down NOA by a linear depreciation rate, assets are faster written off in the initial period and slower written off in the following period. From an accounting perspective, conservatism lessens the booked value of NOA and, as a consequence, increases profitability ratios. Although the business seems to be more efficient from a residual income valuation perspective, firm's net income stays constant. Higher profitability is therefore grounded on the use of accounting choices.

Case IV considers the joint impact of conservatism and growth on accounting profitability. ROA and residual income are lower when they occur together since higher assets (effect of the dominator) are outweighed by the effect in the numerator (higher income).

TABLE 5

Numerical example - the influence of conservative accounting and growth on accounting profitability

			Initial Condition: Straight-line depreciation and no growth in Investments				**Growth Condition: Straight-line depreciation and growth in Investments**				**Conservatism Condition: Accelerated depreciation and no growth in Investments**				**Conservatism and Growth Condition: Accelerated depreciation and growth in Investments**			
			Initial Year	***Forecast Periods***			***Initial Year***	***Forecast Periods***			***Initial Year***	***Forecast Periods***			***Initial Year***	***Forecast Periods***		
			T_0	**F_1**	**F_2**	**F_3**	**T_0**	**F_1**	**F_2**	**F_3**	**T_0**	**F_1**	**F_2**	**F_3**	**T_0**	**F_1**	**F_2**	**F_3**
Financial Year	**NOA**	T_0	50				50				40				40			
		F_1		50				60				40				48		
		F_2			50				72				40				57,6	
		F_3				50				86,4				40				69,12
			50	*50*	*50*	*50*	*50*	*60*	*72*	*86,4*	*40*	*40*	*40*	*40*	*40*	*48*	*57,6*	*69,12*
	REV	T_0	50	55			50	55			50	55			50	55		
		F_1		50	55			60	66			50	55			50	66	
		F_2			50	55			72	79,2			50	55			72	79,2
		F_3				50				86,4				50				86,4
			50	*105*	*105*	*105*	*50*	*115*	*138*	*165,6*	*50*	*105*	*105*	*105*	*50*	*115*	*138*	*165,6*
	DEP	T_0	50	50			50	50			60	40			60	40		
		F_1		50	50			60	60			60	40			72	48	
		F_2			50	50			72	72			60	40			86,4	57,6
		F_3				50				86,4				60				103,68
			50	*100*	*100*	*100*	*50*	*110*	*132*	*158,4*	*60*	*100*	*100*	*100*	*60*	*112*	*134,4*	*161,28*
Income Statement	**REV**		50	105	105	105	50	115	138	165,6	50	105	105	105	50	115	138	165,6
	EXP		50	100	100	100	50	110	132	158,4	60	100	100	100	60	112	134,4	161,28
	NI		0	5	5	5	0	5	6	7,2	-10	5	5	5	-10	3	3,6	4,32
	ROA			10,0%	10,0%	10,0%		10,0%	10,0%	10,0%		12,5%	12,5%	12,5%		7,5%	7,5%	7,5%
	RI			0	0	0		0	0	0		1	1	1		-1	-1,2	-1,44

Notes:

This table shows a numerical example of how conservatism and growth influence the residual income valuation model over four years (T_0 – F_3). The table on the left side represents the base case without influences from growth and conservatism (10% assumed return). The following two cases consider the influence of conservatism (modeled as accelerated depreciation of 60% yr 1 and 40% yr 2 / 10% return) and growth (20% growth in investments / 10% return), respectively. The case on the right side depicts the joint influence of conservatism and growth (accelerated depreciation 60% yr 1, 40% yr 2 / 20% growth in investments / 10% return). ROA and residual income are lower with growth in investment than with constant investment because higher assets (effect of denominator) are dominated by higher income (effect of numerator) in the later years.

This numerical example shows that accounting profitability sensitively reacts towards accounting choices. Particularly, conservative accounting interacts with other factors (e.g. growth in assets) in such manner that profitability could get bloated or deflated. To further amplify these impacts on profitability forecasts, I expand the numerical example from above with a Monte Carlo simulation. I assume that the forecast periods $F_1 – F_3$ are not observable as in the numerical example of Table 5. Based on the initial year (T_0), I simulate forecasts for these three upcoming periods to predict future residual income. For estimating the current firm value, I use residual income valuation to calculate the net present value of the firm. I consider four scenarios where I incorporate different information about the fundamental performance and the accounting system of a firm. In particular, I simulate how different levels of growth in assets, earnings persistence, and depreciation rates (conservative accounting) affect a firm valuation. For all scenarios, I use realistic assumptions for all firm specific data. I finally run the simulation within different industry clusters.[1]

To simulate the impact of conservatism, growth, and persistence on a forecast of future profitability, I consider a firm which generates revenues and costs (depreciation charges) in each period. Data is only available for the initial year (T_0). In order to estimate the present value of a firm, I predict residual income for the next three upcoming periods ($F_1 – F_3$). Growth, conservatism, and persistence are exogenous variables in my model. This specification is considered for competitive industries where each firm sustains earnings, invests in assets, and applies conservative accounting choices dependent to the respective industry peers. For each single observation, I simulate individual parameters for conservatism, growth, and persistence which are then constant in upcoming periods ($F_1 – F_3$). For example, if firm's assets grow by 5% after year T_0, they will remain growing by 5% over the entire simulated period. The same applies to the estimated parameters for conservatism and persistence. The present value of each firm is then the sum of residual income from period $F_1 – F_3$ where the risk-free rate is consistently set to 10%.

Conservatism is measured by the C-Score (see Penman and Zhang 2002 for a definition). The C-Score is the sum of capitalized R&D, advertising expenses, and LIFO reserves scaled by NOA. Like suggested by Balachandran and Mohanram (2011), I

[1] For more realistic assumptions, I extract parameters for conservatism, growth, and persistence from a historical data set from the COMPUSTAT universe. The sample comprises 19,139 U.S. firm-year observations between 2000 through 2010. I separate firms among the two-digit Global Industry Classifications Standard (GICS) and delete those which belong to the financial sector (GICS #40). I delete firm-year observations with missing values for calculating the proxies. To further reduce concerns that outliers bias my proxies, I winsorize my proxies on the 1% level from both sides. I estimate proxies for conservatism, growth, and persistence for each industry on a yearly basis. Finally, I extract the median and the standard deviation for each industry over the entire sample period.

capitalize and amortize R&D over 5 years and advertising expenses over 2 years, using sum-of-years-digits amortization.[2]

Earnings persistence is measured as the slope coefficient $\phi 1$ in the following regression model (Barton et al. 2010):

$$\text{Net Income}_{t} = \phi_0 + \phi_1 \text{Net Income}_{t-1} + \varepsilon_t$$

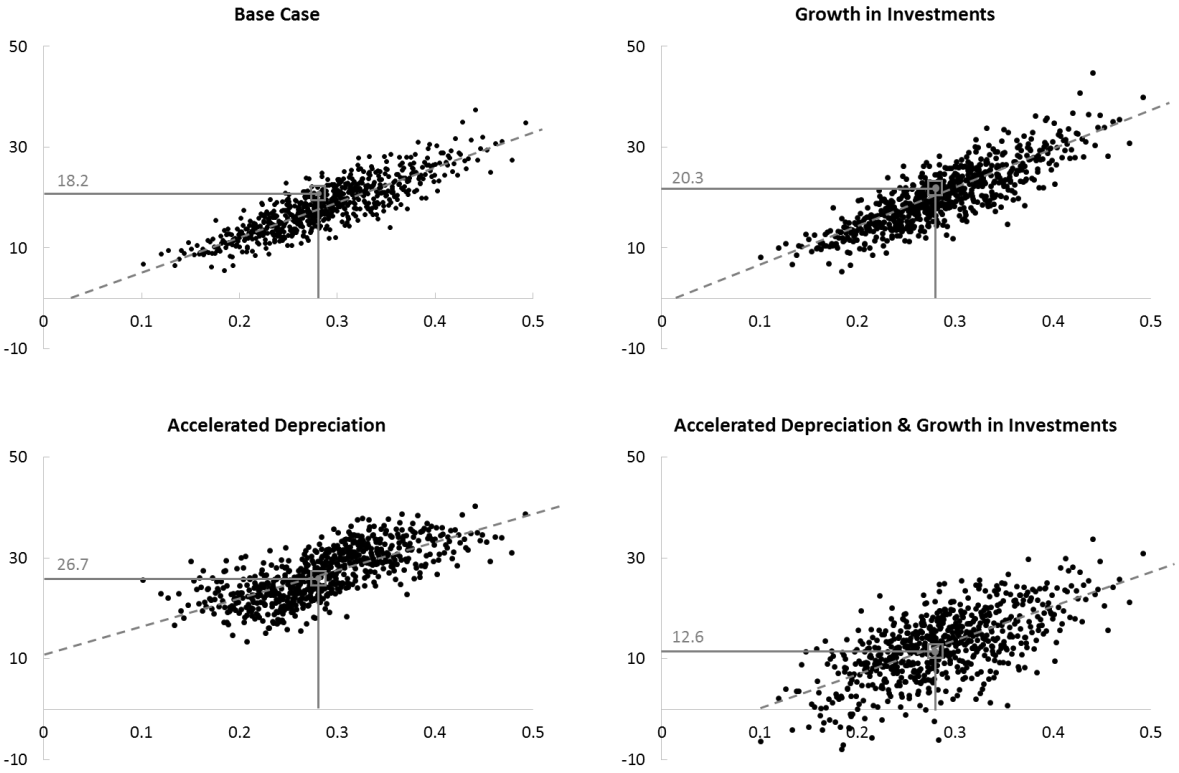
Last, I define growth as the yearly percentage change in NOA since operating activities and operating assets mainly drive firm value (Ohlson 1995). Following the numerical example, I begin my simulation with comparable values for NOA (150) and REV (150) (see Table 5). These financial figures are then exposed to proxies of conservatism, growth, and persistence by their industry mean, respectively.[3]

[2] Sum-of-years-digits amortization is an accelerated method for determining an asset's depreciation rate. A two-year depreciation period, for example, means that the sum-of-year-digits are obtained by adding the sum of the expected years of depreciation (1+2). Each year is then divided by this sum to determine the depreciation rate (e.g. year 2 = 2/3 ~ 0.66%).

[3] For each single observation, we simulate individual parameters for conservatism, growth, and persistence which are then held constant for the upcoming periods (F1 – F3). The calculation logic equals the example presented in Table 5. Each simulation starts with the same values for NOA (150) and REV (150).
The respective proxies for conservatism and growth are the industry median values as they are extracted from the U.S. data set in the sample period between 2000 through 2010. For each simulated case, I subject the respective proxy to a normally distributed variation factor. This variation factor is simulated based on a normal distribution where the median equals the respective industry median and the variance equals the respective variance within the industry. To simulate earnings persistence, I additionally subscribe a constant amount to NI in each year based on the persistence factor. Higher simulated values for persistence increase the additional NI share. This way, I depict more persistent earnings where a certain share of earnings is transferred into the next fiscal year. The simulation thus follows the numerical example presented in Table 5 modified by varying values for growth, conservatism, and persistence for each simulated observation.

FIGURE 2

Simulated firm valuation under conservative accounting, growth, and persistence



Notes:
This figure draws the distribution of 9,000 simulated firm valuations as outlined in the footnote for the simulation framework. To ensure a better overview, the figure just plots a fraction of all simulated draws where each point represents 10 simulated draws. I run 1,000 simulations within each of nine industry sectors (9,000 draws in total). The horizontal axis plots the persistence of earnings. Values of persistence close to 1 indicate highly persistent earnings, while values close to 0 indicate transitory earnings. The vertical axis plots the simulated sum of aggregated RI between periods F1 – F3.

Figure 2 presents estimates of the forecasted firm value. The upper left quadrant presents the base case of my simulation where the initial values for NOA, REV, and DEP are affected by industry differences only. The upper right quadrant considers a constant growth in assets under neutral accounting. The lower left quadrant simulates the effect of conservative accounting in a steady-state (no-growth case). The lower right quadrant finally includes both cases, growth in assets under conservative accounting. The point estimates show different distributions with different mean values for each case. By comparing the growth in investment case (simulated mean value of 20.3) with the base case (simulated mean value of 18.2), one can observe similar valuation results.[4] By adding conservatism to the valuation framework, it crucially depends whether one expects growing or non-growing assets. By assuming conservatism without further investment in assets, one leverages the

[4] Statistics from t-tests indicate that the mean values are not significantly different.

estimated value of a firm since reduced assets temporarily increase accounting profitability. The mean simulated value is 26.7. On the contrary, if we assume the choice of conservative accounting principles in combination with growing investments in firms' assets, the decreasing accounting profitability reduces the estimated firm value (simulated mean value is 12.6). As pinpointed in the numerical example, accounting profitability and residual income are lower with growth in investments under conservative accounting than with constant investments because the effect of the denominator (higher assets) is dominated by the effect of the numerator (higher income) in the later years.

This simulation illustrates the impact of the accounting system on the prediction of a firm's profitability. Keeping the firm performance constant across all cases, the mean value of the simulated estimation differs by over 100% (e.g. accelerated depreciation & growth in investments case: 12.6 versus accelerated depreciation case: 26.7). The only differences supposed by the Monte Carlo simulation are assumption about firms' future growth, persistence of earnings, and accounting conservatism.

3.3 The Incorporation of Persistence, Growth and Conservatism into Profitability Forecasting Models

After demonstrating the impact of the accounting systems on the prediction of firms' profitability, I survey whether and to what extent the FSA literature incorporates the level of earnings persistence, growth, and conservatism into forecasting models. In addition, I distinguish whether or not the authors are aware or unaware of using a particular parameter as a proxy for earnings persistence, conservatism, or growth. This should reveal if a ratio is consciously used as a control parameter or just coincidentally incorporated through a widespread array of different ratios. As a result, I want to shed light how FSA literature incorporates findings of the F-O framework into forecasting models. Lastly, I outline the kinds of ratios that are used within the forecasting models. Table 6 summarizes the incorporation of earning persistence, growth, and conservatism in prior research studies.

TABLE 6

Overview of incorporation of growth, earnings persistence, and conservatism into forecasting models

		Growth	Persistence	Conservatism
Unstructured Approaches	*overall*	28.6%	33.3%	16.7%
	aware	75.0%	64.3%	85.7%
	unaware	25.0%	35.7%	14.3%
Structured Approaches	*overall*	17.6%	47.1%	5.9%
	aware	100.0%	87.5%	100.0%
	unaware	0.0%	12.5%	0.0%
Theory-Driven Approaches	*overall*	27.3%	45.5%	30.3%
	aware	100.0%	86.7%	100.0%
	unaware	0.0%	13.3%	0.0%

Notes:
This table gives an overview of the incorporation of growth, earnings persistence, and conservatism into the surveyed literature of this review. I distinguish for each parameter between three different cases: fist, I analyze whether a study incorporates a proxy for the respective category (overall). The second and third case analyze whether a study is aware (unaware) that a parameter in a forecasting model controls for growth, persistence, or conservatism. This overview is based on 52 studies that were already discussed in chapter 2 of this review.

Ex ante, I would assume that growth plays the most crucial role in forecasting models. Contrary to this assumption, the FSA literature incorporates earnings persistence as the most frequently included parameter in profitability forecasts. Accounting conservatism represents the least included parameter. I hypothesize that this is the case because of the difficult nature to measure accounting conservatism. In addition, the distribution of the incorporation varies for each parameter along the FSA approaches. For instance, conservatism is more often incorporated by *theory-driven profitability forecasting approaches*. This is mainly grounded in the theoretical background of this type of literature since influences of the accounting system take a central position for this research. Further, I find differences between the studies by examining whether they are aware or unware of using certain proxies.

By definition, *unstructured profitability forecasting approaches* add parameters in an unstructured modality. The weak structure also reflects that most of such studies do not explain in detail why a certain ratio is added to the forecasting model. About one third of studies using *unstructured profitability forecasting approaches* that control for earnings persistence do not explain why they include a certain variable in a forecasting model. As opposed, studies using *theory-driven profitability forecasting approaches* build models in the

knowledge that forecasts based on accounting information can be enhanced with these influencing factors.

Next, I analyze the joint application of parameters which proxy for the F-O framework. For this purpose, I rank studies by the number of proxies included in forecasting models. Table 7 shows the number of parameters included which control for growth, persistence, and conservatism.

TABLE 7

Overview of number of F-O parameters (growth, persistence, and conservatism) included into forecasting models

	Number of parameters included			
	0	**1**	**2**	**3**
Unstructured Approaches	27,3%	18,2%	18,2%	36,3%
Structured Approaches	36,4%	36,4%	9,1%	18,1%
Theory-Driven Approaches	5,3%	21,1%	63,2%	10,4%

Notes:
This table gives an overview of proxies for growth, persistence, and conservatism included in the surveyed literature. The overview is based on 52 studies that were already discussed in chapter 2 of this review.

Studies using *unstructured profitability forecasting approaches* comprehensively control (36%) for all three influencing parameters in their forecasting models. Even if the integration of control variables is often performed unconsciously, the significant amount of ratios permits a broad coverage of all three parameters. Studies using *structured profitability forecasting approaches*, on the contrary, prevailingly control either for one parameter or even for none. This unfolds the insufficient control of forecasting models which are purely based along DuPont decomposition or other structured disaggregation approaches in respect of controlling for growth, conservatism, or persistence. This is the more astonishing since such structured decompositions of ratios that are built on one another might reveal the influence of these factors on forecasts' accuracy from a holistic view. Studies using *theory-driven profitability forecasting approaches* incorporate two parameters on average. But in comparison to *unstructured and structured profitability forecasting approaches*, the influence of the F-O parameters is more pronounced. In particular, the joint influence of conservatism and growth is a controversial analyzed issue (e.g. Penman and Zhang 2002; Balachandran and Mohanram 2011). Most of the studies thereby add at least one parameter to their FSA

model. Especially, *theory-driven profitability forecasting approaches* include accounting influences into forecasts.

Growth is said to be the engine of future firm performance and sustainable business performance (e.g. King et al. 1988). Growth can be measured in various ways. In studies using *unstructured profitability forecasting approaches*, growth is primarily proxied by growing revenues (e.g. Ou and Penman 1989), by R&D investments (e.g. Lev and Thiagarajan 1993; Ou 1990), or by other capital expenditures (e.g. Beneish et al. 2001; Mohanram 2005) relatively to the growth in firms' assets. Hereby, growth is often seen as a positive indication for future profitability since it reflects investments into future cash flow generating units. In contrast, *structured or theory-driven profitability forecasting approaches* find that growth correlates with temporarily weaker firm performance. Previous studies claim that growth distorts forecasts because it is associated with conservatism.[5] By having both growing assets and conservative accounting, earnings get depressed (e.g. Rajan et al. 2007; Beaver and Ryan 2000; Penman and Zhang 2002). The different approaches to include growth in forecasts as either a more negative sign, or alternatively, as an indication for positive firm performance reflects once more the fundamental difference between these categories. Summarizing all possible influences stemming from growth, I conclude that growth is a highly relevant factor which accordingly should be incorporated into forecasting models (Fairfield et al. 2003; Penman and Zhang 2002).

Kothari (2001) broadly defines conservatism as asymmetry in the speed with which accounting numbers reflect economic gains and losses or earnings reflecting 'bad news more quickly than good news'. However, there is neither a prevalent method of measurement nor a commonly accepted interpretation of accounting conservatism. Following the accounting-based valuation literature, FSA research characterizes conservatism mainly as the difference between the market value and book value of equity as the accounting system depresses value through the asymmetric recognition of profit and loss as well as the non-fair value measurement of certain assets. Due to measurement issues of conservatism, FSA literature has seen controlling for conservatism as minor necessity for forecasting models. Furthermore, proxies for conservatism were found not to be significant for prediction models in earlier studies (e.g. Frankel and Lee 1998). This is the reason why proxies for conservatism are rarely used in *unstructured profitability forecasting approaches*. However, those studies examine certain types of expenses with higher margins of discretion such as R&D, advertising costs or capital expenditures (e.g. Mohanram 2005) in order to proxy if the

[5] For instance, Lev and Zarowin (1999) find decreasing value relevance with an increasing level of R&D expenses.

gap between book and market value is more likely due to conservative accountancy behavior. In contrast, *theory-driven profitability forecasting approaches* actively search for mispriced companies as a consequence of markets inability to evaluate the effect of conservative accounting practices properly (e.g. Beaver and Ryan 2000; Penman and Zhang 2002). Furthermore, studies using *theory-driven profitability forecasting approaches* discuss several proxies in order to measure the degree of applied conservatism. In contrast, studies using *unstructured profitability forecasting approaches* favor a dichotomous separation into conservative and liberal accounting practices. Despite their exposure towards balance sheet and income statement information, *structured profitability forecasting approaches* insufficiently incorporate conservatism proxies into forecasting models.

As presented above, when forecasts of profitability are performed, conservatism and growth can give some indication with respect to whether future profitability could be bloated or deflated. At the heart of forecasting, however, it is the persistence of abnormal (residual) income which directly quantifies future profitability. The extensive survey of financial executives operated by Graham et al. (2005) ascertains the importance of stable earnings trends for predicting future earnings and, ultimately, profitability. As presented above, ratios which control for persistence are frequently used in prior FSA research. However, while *unstructured profitability forecasting approaches* mainly concentrate on bottom-line figures such as (the change in) current earnings, *structured profitability forecasting approaches* take advantage of disaggregated models to isolate the main divers of firms' persistence. In contrast, *theory-driven profitability forecasting approaches* address this issue by including recent accounting research insights that is likely to affect earnings persistence (such as the separation of financing and operating activities, or respectively, the level of accruals).[6]

I conclude that earnings persistence, growth and conservatism already take an important position in the FSA literature. However, ratios for these are not consistently used in the literature. Furthermore, research on earnings persistence, profitability and growth requires the following future research focus. First, information on earnings persistence, profitability and growth is usually taken from a firm's balance sheet and/or income statement only. But in fact, there are additional sources beyond pure balance sheet/income statement information which could be worth researching. For instance, growth and persistence are strongly correlated with industry peer groups and benchmark. Industry specific analyses could add information to forecasts in providing more branch expertise to the models. Fairfield et al. (2009) already provide evidence on the necessity to break down forecasts on industry levels. By the same token, FSA models could be extended by including qualitative

[6] See for instance Esplin et al. (2014), Lim (2014).

information on persistence, growth and conservatism from footnote disclosures (e.g. Thomas and Zhang 2006). Second, prior literature has neglected the influence of earnings persistence on growth and conservatism what is a central aspect of the Feltham and Ohlson (1995) model that should be considered to fully bridge the gap between accounting valuation theory and financial statement analysis based forecasting.

4. Summary and Future Research

In this literature review, I highlight the recent advances in financial statement-based fundamental analysis research (FSA) literature to forecast firm profitability. My primary objective is to evaluate whether accounting information from publicly available financial statements helps investors to allocate resources and to facilitate investment decisions. In this matter, I attach importance to research that is dedicated to forecasting future earnings and stock returns. Much has been learned since Ou and Penman (1989) offered evidence that forecasting is also matter of accounting and since Bernard (1989) identified financial statement analysis as relevant research area. Since then, the FSA literature has grown by an ample number of studies. My survey provides a critical review of the most contributing studies of this field of research.

The analysis highlights that the structure of financial statement-based forecasts has shifted from *unstructured* forecasting models, to more *structured* approaches, and finally towards *theory-driven* models that incorporate latest findings from accounting research. Furthermore, I show that the forecasting power of accounting information depends on many factors. For instance, combinations of accounting ratios (e.g., the forecasting-relevance of one ratio can partly depend on a second ratio), different variable specifications (absolute versus change variables), institutional and macroeconomic conditions, or firm specific characteristics determine the explanatory power of accounting ratios to predict future profitability. However, I note that the FSA research has changed from being considered as ‘kitchen-sink’ approaches (Richardson et al. 2010) to becoming an established research stream in the accounting literature. I also note the progress that FSA models more frequently incorporate latest finding from accounting research.

Next, I review major issues and validity concerns that are central on FSA research. In particular, I examine theoretical and technical issues of forecasting models. Theoretical issues comprise whether forecasts are in line with findings from previous literature. I analyze if studies incorporate value-relevant information and if they strip off information that was not

found to be incrementally useful for the accuracy of forecasts. Technical issues mainly address statistical issues and measurement techniques. In conclusion, external validity issues are the main concern in the FSA literature since findings are often based on specific markets (predominantly US markets) and narrow timeframes. Thus, it is not clear whether and to what extent these findings can be transferred to other settings.

In subsequent analyses using a Monte Carlo simulation, I demonstrate the influence of earnings persistence, accounting conservatism, and growth on firm value (Feltham and Ohlson 1995). This simulation clearly demonstrates that firm value can vary as a consequence of fundamental performance and the configuration of the accounting system. In particular, conservatism leverages the estimated value of a firm since a reduction in net assets temporarily increases accounting profitability (measured as return on equity), while the combination of conservative accounting principles with growing investments in firms' net assets leads to a reduction in accounting profitability, and thus, ultimately results in a lower firm value estimation. Surprisingly, I find that the current literature does not pay full attention with respect to earnings persistence, growth and conservatism as it frequently neglects their incorporation in forecasting models.

Finally, I want to outline that research into FSA is still left with a great number of important yet unanswered questions of which some of them have been mentioned above. Specifically, the following future research avenues turn out to be highly relevant. First, the introduction of mandatory IFRS adoption and simultaneous (subsequent) changes to the enforcement of financial reporting have changed the persistence, conservatism, and growth in earnings numbers (e.g., Barth et al. 2008; Atwood et al. 2011; Ahmed et al. 2013). As such, it is important to understand the impact of mandatory IFRS adoption on profitability forecasting, and respectively, firm valuation. In the same vein, the question arises whether and how any change in the predictive power of accounting numbers has been incorporated in analysts' forecasts of earnings (Bae et al. 2008; Tan et al. 2011; Horton et al. 2013). Second, FSA still misses a systematic approach for incorporating conservatism and growth into forecasting models. Both parameters affect earnings quality (Penman and Zhang 2002). By finding ways to incorporate such influences into forecasting models, FSA literature would advance in understanding how earnings quality factors moderate the accuracy of profitability forecasts. Third, FSA models need to be extended and/or adjusted to certain industries (in particular, the financial services) as well as macroeconomic conditions (Mohanram 2005; Richardson et al. 2010). With respect to the macroeconomic conditions, prior research seems to have completely ignored the importance of economic cycles when predicting future firm profitability. Also, these economic cycles are likely to vary across countries and/or

industries which make them potentially relevant for forecasting models. Fourth, forecasting models require adjustments when M&A transactions are highly likely since firms' earnings quality is affected during acquisition processes due to various influences (e.g. earnings management, special costs, goodwill, restructuring charges etc.; see Raman et al. 2013). Likewise, models require adjustments when firms shift their focus from one business segment to another, or respectively, when different business segments develop differently. Fifth, times series prediction models are biased when firms need to report losses (in particular if early-stage high growth companies are included in the cross-section of firms).[7] Sixth, a new stream of research starts to explore the measurement of risk with accounting ratios. Penman and Reggiani (2013) show that the earnings-to-price and book-to-price ratios forecast both earnings growth and the risk that is associated with growth. Furthermore, valuation and forecasting assume required returns (discount rates) for determining firms' risk premium. Asset pricing models from the finance literature usually serve as supply in this respect. Risk quantification on the basis of financial statement information is still a wide open research field that can tie on promising ideas from the beginning of positive accounting research where risk determination was not exclusively part of finance research (see e.g. Rosenberg and McKibben 1973). As an extension, future research could also try to exploit the information content of accounting ratios to predict future stock volatility as a risk-dependent outcome. Seventh, FSA literature is scarce on long-term predictions of earnings. Existing research is almost exclusively focused on one-year ahead forecasts although findings indicate the importance of long-term forecasts (e.g. Ready et al. 2010). Eighth, FSA models could be extended by including qualitative information on persistence, growth and conservatism from footnote disclosures (e.g., Thomas and Zhang 2008). In that regard, textual analysis might be especially promising (Berger and Hann 2007; Li 2010) as footnote information can be more effectively processed after the introduction of XBRL (see e.g. Blankespoor et al. 2014; Debreceny 2010).

Last, there are a number of econometric issues which should be further investigated as they are likely to significantly improve the accuracy of profitability forecasting models (Richardson et al. 2010). At first, FSA research should clearly distinguish between ex-post in-sample explanations of economic associations and ex-ante out-of-sample predictions. In-sample regressions are not tests of forecasting accuracy and may lead to wrong inferences concerning forecast power (Lev et al. 2010). Lev et al. (2010) motivate research not merely to investigate the explanatory power of forecasts in-sample but rather as a challenge that

[7] Losses usually have an infrequent nature and occur unexpectedly. From a statistical point of view, such variance effects and structural breaks are additional sources of forecast error biases. The statistical forecasting literature suggests models and adjustments to offset such structural breaks to make forecasts more robust against unexpected losses (see e.g. Clements and Hendry 2001).

real investors have to face. This is to test the usefulness of a model not only backward but also forward in an out-of-sample prediction. Indeed, it is only the out-of-sample tests which can document the accuracy of a particular forecasting model. Furthermore, abnormal returns are frequently calculated excluding the advancements of finance (size, growth, and momentum factors, etc.). Again, this may lead to wrong inferences concerning forecast power and the implementation of a particular trading strategy. In addition, trading costs of those trading strategies are typically neglected (Richardson et al. 2010). Next, the ratios used in forecasting models are regularly scaled by total assets and/or the book (market) value of equity. As Barth et al. 2009 point out, scaling can lead to biased coefficients under certain circumstances, and thus, greatly diminishes forecast accuracy. Alternatively, proxies for firm size should be separately excluded for any forecasting model. Furthermore, the non-fulfillment of the orthogonality condition[8] leads to a bias in the predictors' coefficient, again, reducing the power of the forecasting model. As such, alternative estimation techniques such as bootstrapping, simulation models and the like should be considered for forecasts of a firm's profitability (see Greene 2004).

Finally, I believe that financial statement-based fundamental analysis research has provided considerable findings by demonstrating how accounting information can be used to forecast future firm performance. I am hopeful that researches and practitioners will benefit from my literature review and that my work facilitates further advancements for the accounting profession.

[8] The orthogonality condition requires independent variables that affect a dependent variable in a regression model to be uncorrelated (orthogonal). If this is assumption does not hold, the covariance of non-orthogonal variables could form an inner product that has the same effect on the dependent variable.

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Teil 3

Financial Statement-Based Forecasts and Analyst Forecasts of Profitability: The Effect of Mandatory IFRS Adoption

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Financial Statement-Based Forecasts and Analyst Forecasts of Profitability: The Effect of Mandatory IFRS Adoption

ABSTRACT

This study examines whether mandatory IFRS adoption is associated with an increase in the accuracy of financial statement-based models for forecasting profitability. The study also examines the relation between analyst forecast accuracy and financial statement-based forecast accuracy around mandatory IFRS adoption. We find significant improvement in financial statement-based forecast accuracy around mandatory IFRS adoption. We find significant improvement in analyst forecast accuracy around mandatory IFRS adoption only in countries that concurrently made substantial improvements to reporting enforcement. We also find that the improvement in analyst forecast accuracy is associated with the improvement in financial statement-based forecast accuracy. We show that analysts place the same weight on financial statement-based forecasts after mandatory IFRS adoption in countries with concurrent changes in enforcement and place less weight on financial statement-based forecasts after mandatory IFRS adoption in countries without concurrent enforcement changes. Finally, we document that financial statement-based forecasts provide incremental information over analyst forecasts for explaining year-ahead profitability for firms in countries that mandatorily adopted IFRS, whether or not the country bundled IFRS adoption with concurrent changes in enforcement. These findings are important for understanding the impact of mandatory IFRS adoption on the predictive ability of financial statements and for understanding analysts' use of financial statements around mandatory IFRS adoption.

Keywords: mandatory IFRS adoption, analysts, forecasts, future profitability

JEL classification: M41, G17

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I. Introduction

The mandatory adoption of IFRS in the European Union (EU) and around the world represents the most influential accounting system change in recent history (Christensen et al. 2013; Cascino and Gassen 2014), and accordingly, has been extensively investigated by academic research. The empirical evidence generally suggests positive capital market and macroeconomic consequences of mandatory IFRS adoption (see Bruggemann et al. 2013 for an overview). In particular, research suggests that mandatory IFRS adoption is associated with lower information uncertainty (Leuz and Verrecchia 2000) and greater value relevance of accounting information (Bartov et al. 2005). Despite the significant impact of IFRS adoption on accounting recognition and measurement rules, the literature has provided little insight into the effect of mandatory IFRS adoption on the usefulness of financial statements. While research has examined the effect of mandatory IFRS adoption on accounting quality, the evidence is mixed (Atwood et al. 2011; Gebhardt and Novotny-Farkas 2011; Barth et al. 2012; Ahmed et al. 2013), and the research has not examined the effect of mandatory IFRS adoption on the predictive ability of the financial statements for future profitability.

Research has, however, examined the effect of mandatory IFRS adoption on analyst forecasts of future profitability, and suggests that mandatory IFRS adoption is associated with lower analyst forecast errors (Byard et al. 2011; Tan et al. 2011; Horton et al. 2013; and Houqe et al. 2014). However, the literature has not provided insight into the mechanism through which mandatory IFRS adoption has enhanced analysts' ability to forecast profitability. While some studies suggest that increased disclosure quality (Hope 2003a; Hope 2003b; Ball 2006; Barth et al. 2008; Glaum et al. 2013) and increased comparability (Bae et al. 2008; Tan et al. 2011; Horton et al. 2013) contribute to the increased analyst forecast accuracy around mandatory IFRS adoption, research has not examined whether analyst forecast accuracy is associated with the accuracy of forecasts based on the financial statements.

In this study, we provide insight into the effect of mandatory IFRS adoption on accounting quality by examining the ability of financial statement-based models to forecast firm profitability. We also provide insight into whether the improvement in analyst forecast accuracy around mandatory IFRS adoption is associated with an improvement in the accuracy of financial statement-based forecasts. Thus, we investigate the mechanism through which mandatory IFRS adoption leads to improved analyst forecast accuracy (Fogarty and Rogers 2005; Abarbanell and Bushee 1997; Soliman 2008). Finally, we investigate whether analysts place greater weight on financial statement-based forecasts

after mandatory IFRS adoption, consistent with them recognizing the improved predictive ability.

Prior research suggests that IFRS generally restricts a firm's recognition and measurement choices relative to local standards (Ashbaugh and Pincus 2001). We argue that a restricted set of possible accounting methods should lead to more predictable accounting information (Ashbaugh and Pincus 2001) and therefore to increased accuracy of financial statement-based forecasts of profitability. Accordingly, we predict that improved accuracy of financial statement-based forecasts is a contributing factor to the overall improvement in analyst forecast accuracy around mandatory IFRS adoption. Thus, we assert that the increase in analyst forecast accuracy around mandatory IFRS adoption stems not only from higher levels of disclosure and comparability (Ball et al. 2003; Ball 2006; Holthausen 2009), but also from improved accuracy of financial statement-based forecasts after mandatory IFRS adoption. Finally, we predict that analysts place greater weight on financial statement-based forecasts after IFRS adoption.

Our empirical tests are based on an international sample of firms from 22 countries in a pre-IFRS and a post-IFRS adoption period. We also include firms in the US for the same periods as a control sample. We construct financial statement-based forecasts of accounting return on equity (ROE) following recommendations of financial statement analysis textbooks (Penman 2012; Lundholm and Sloan 2006) and research (Fairfield et al. 1996; Fairfield and Yohn 2001). The forecasting model is estimated by country, within industry, and separately for the pre- and post-IFRS adoption periods using rolling three-year regressions. Using the in-sample parameter estimates, we develop out-of-sample forecasts of ROE and calculate the forecast errors from the financial statement-based model as the difference between the forecast and actual ROE. We use difference-in-differences analyses to test whether the financial statement-based forecast accuracy and the analyst concensus forecast accuracy improved around mandatory IFRS adoption.

We find significant improvement in the accuracy of financial statement-based forecasts from the pre- to the post-IFRS adoption period. We find significant improvement in the accuracy of analyst forecasts around IFRS adoption but only for firms in countries with concurrent changes in enforcement. We also find that the improvement in analyst forecast accuracy is associated with the improvement in the accuracy of financial statement-based forecasts around IFRS adoption; however, the association is not stronger for firms in countries with mandatory IFRS adoption. We show that analysts place the same weight on financial statement-based forecasts after mandatory IFRS adoption in countries with

concurrent changes in enforcement and less weight on financial statement-based forecasts after mandatory IFRS adoption in countries without concurrent changes in enforcement.

Finally, we document that financial statement-based forecasts provide incremental information over analyst forecasts for explaining year-ahead profitability for firms in countries that mandatorily adopted IFRS. This finding holds both for firms in countries that bundled and for firms in countries that did not bundle IFRS adoption with concurrent changes in reporting enforcement. These results suggest that analysts do not place enough weight on financial statement-based forecasts after mandatory IFRS adoption.

This study provides several contributions to the literature on forecasting profitability and standard setting. We find that the mandatory adoption of IFRS is associated with an improvement in the accuracy of financial statement-based forecasts. We also find that mandatory adoption of IFRS is associated with an improvement in analyst forecast accuracy for firms in countries that implemented concurrent improvements in reporting enforcement. Further, we demonstrate that analysts would benefit from placing greater weight on financial statement-based forecasts after mandatory IFRS adoption whether or not the mandatory IFRS adoption is bundled with concurrent improvements in financial reporting enforcement. We also contribute to financial statement analysis research more generally by demonstrating that analyst forecast accuracy is highly associated with financial statement-based forecast accuracy. This finding suggests that prior research may have overlooked an important component of analyst forecast accuracy and that future research should consider this relation in attempting to explain analyst forecast accuracy.

The remainder of this paper is organized as follows. The second section reviews prior literature and develops hypotheses. The third section describes the standard forecasting approach as well as the research design to test whether the enhanced ability of analysts to forecast profitability is associated with a changed accuracy of financial statement-based forecasts following mandatory IFRS adoption. Section IV presents the empirical analyses while section V concludes the paper.

II. Hypotheses Development

A large body of research has investigated the consequences of mandatory IFRS adoption.[1] For example, Barth et al. (2008), Atwood et al. (2011), Barth et al. (2012), and Ahmed et al. (2013) examine the effect of mandatory IFRS adoption on accounting quality,

[1] Soderstrom and Sun (2007) and Bruggemann et al. (2013) provide reviews of the literature.

providing mixed empirical evidence on whether IFRS enhances accounting quality.[2] Further, Christensen et al. (2007), Daske et al. (2008), Armstrong et al. (2010), Li (2010), Muller et al. (2011), Landsman et al. (2012), and Christensen et al. (2013) investigate capital market consequences of mandatory IFRS adoption by examining the effect of IFRS adoption on stock market reactions, the cost of capital, liquidity, and the information content of earnings announcements. The results provide evidence of capital market benefits of mandatory IFRS adoption.[3] Further, mandatory IFRS adoption has been documented to lead to macroeconomic benefits. Amiram (2012), Khurana and Michas (2011), Shima and Gordon (2011), and Beneish et al. (2014) find evidence of an increase in foreign debt and equity investments following mandatory IFRS adoption.

Prior research has also investigated the consequences of mandatory IFRS adoption on analysts' information environment. Byard et al. (2011) investigate the effect of mandatory IFRS adoption on analyst forecast errors and dispersion and on analyst following relative to a control sample of voluntary IFRS adopters. They find that analyst forecast errors and dispersion are significantly reduced around mandatory IFRS adoption. Tan et al. (2011) find that foreign analyst forecast errors decrease from the pre- to the post-IFRS adoption period, and Horton et al. (2013) provide further empirical evidence of a general decrease in analyst forecast errors from the pre- to the post-IFRS adoption period. Based on this prior research, we predict an improvement in analyst forecast accuracy after mandatory IFRS adoption. This leads to our first hypothesis:

H1a: The accuracy of analyst forecasts of profitability improves after mandatory IFRS adoption.

While prior research suggests improvements in analyst forecast accuracy around IFRS adoption, the research provides little insight into the mechanisms that contribute to that improved accuracy (Bae et al. 2008). Some research suggests that the improved accuracy is at least partially attributable to the increase in the quantity of financial information which accompanies IFRS adoption (Ball 2006; Barth et al. 2008; Hope 2003a, 2003b). Others suggest that the increased analyst forecast accuracy could be attributable to increased cross-firm comparability from IFRS adoption (Bae et al. 2008; Tan et al. 2011; Horton et al. 2013; Cascino and Gassen 2014).

[2] The studies examine different dimensions of accounting quality such as value relevance, conservatism, timeliness of loss recognition, earnings management, volatility, earnings persistence, correlations between accruals and cash flows, income smoothing, etc.

[3] Prior research has also investigated the consequences of mandatory IFRS adoption in debt markets (Wu and Zhang 2009; Bhat et al. 2011; and Ball et al. 2013).

We note that the prior research has not provided a more direct explanation for the enhanced analyst forecast accuracy following mandatory IFRS adoption. We provide a fundamental reason for the improved analyst forecast accuracy around mandatory IFRS adoption. That is, we argue that the conversion to IFRS is likely to affect the usefulness of financial statements for forecasting profitability (Bouwman et al. 1987; Fogarty and Rogers 2005; Mira and Taylor 2011).[4] We therefore argue that the switch from domestic GAAP to IFRS is likely to improve the accuracy of financial statement-based forecasts, and that this is a contributing factor to the overall improvement in analyst forecast accuracy around IFRS adoption. The switch from domestic GAAP to IFRS typically not only increases a firm's level of disclosure, but also restricts a firm's accounting measurement and recognition choices (Ashbaugh and Pincus 2001).[5] As the number of possible accounting methods is reduced, reported accounting numbers become more predictable, and thus are arguably more useful for financial statement-based forecasts of profitability. While a reduced number of possible accounting choices could result in less predictive financial statements if managers used the accounting choices to provide valuable information, we predict that more restrictive rules lead to more accurate financial statement-based forecasts after mandatory IFRS adoption.[6] This leads to the following hypothesis:

H1b: The accuracy of financial statement-based forecasts of profitability improves after mandatory IFRS adoption.

Prior research suggests that some of the benefits of mandatory IFRS adoption are confined to firms from countries with concurrent changes in financial reporting enforcement. For example, Christensen et al. (2013) find that liquidity benefits are limited to the five EU countries (Finland, Germany, the Netherlands, Norway, and the U.K.) that made substantive changes to their enforcement of financial reporting upon mandatory IFRS adoption.[7] We argue that changes in the enforcement regime are not only likely to affect whether and how

[4] We argue that profitability prediction is an important criterion for assessing accounting quality because FASB asserts that accounting information should be "useful in assessing the amount, timing, and uncertainty of its future cash flows" (FASB 2008, 10) and that users interested in future cash flows are primarily interested in "information about [a firm's] earnings rather than information directly about its cash flows" (FASB 1978, 13). In addition, forecating profitability is fundamental to valuation. Bernard (1995, 736) suggests that profitability prediction "is tantamount to the ability to approximate current value" and Nissim and Penman (2001, 124) note that "the analysis of current financial statements should be guided by the 'predictive ability' criterion: any enhancement that improves forecasts is an innovation."

[5] The increase in disclosure has been documented by Ernst & Young's (2007) survey of IFRS annual reports by major European firms. The survey as well as Tan et al. (2011) attribute the increased level of disclosure to the greater IFRS disclosure requirements in comparison to most European domestic GAAPs.

[6] Other factors likely to affect the accuracy of financial statement-based forecasts following mandatory IFRS adoption are the change in the use of fair-value measurement, conservatism, and accrual accounting. It is not obvious *ex ante* whether these factors increase or decrease the predictive ability of financial statements. Please refer to Ernstberger et al. (2008) for a detailed discussion.

[7] Thus, Christensen et al. (2013, 25) conclude that the "results make it unlikely that the change in accounting standards is the primary or even an important driver … around IFRS adoption".

the capital markets are affected by mandatory IFRS adoption, but are also likely to affect post-IFRS financial reporting quality (Soderstrom and Sun 2007). Specifically, we argue that improved financial reporting standards are unlikely to result in improved financial reporting quality unless there is also an improvement in the country's enforcement upon mandatory IFRS adoption. We therefore hypothesize that the accuracy of analyst forecasts and the accuracy of financial statement-based forecasts improve around mandatory IFRS adoption only in countries with concurrent improvements in financial reporting enforcement. This leads to our second set of hypotheses:

H2a: The improvement in the accuracy of analyst forecasts of profitability following mandatory IFRS adoption is conditional on concurrent changes in enforcement.

H2b: The improvement in the accuracy of financial statement-based forecasts of profitability following mandatory IFRS adoption is conditional on concurrent changes in enforcement.

We argue that the general increase in analyst forecast accuracy may be driven not only by the higher level of disclosure and greater comparability that accompanies mandatory IFRS adoption (Ball et al. 2003; Ball 2006; Holthausen 2009), but also by the improved financial statement predictive ability that accompanies IFRS adoption.We predict that the accuracy of analyst forecasts is likely to be related to the accuracy of financial statement-based forecasts and, therefore, that the improvement in analyst forecast accuracy around mandatory IFRS adoption is likely to be associated with the improvement in the accuracy of financial statement-based forecasts. This relation reflects a fundamental mechanism that could explain the general change in analyst forecast accuracy around mandatory IFRS adoption. This leads to our third hypothesis:

H3: Changes in analyst forecast accuracy are positively associated with changes in the accuracy of financial statement-based forecasts of profitability around mandatory IFRS adoption.

Finally, we hypothesize that analysts are likely to place greater reliance on financial statement-based forecasts after mandatory IFRS adoption. That is, we argue that if IFRS adoption leads to improved accuracy of financial statement-based forecasts, then analysts should place greater weight on these forecasts after mandatory IFRS adoption. We, therefore, predict that analyst forecasts of profitability have a greater association with the financial statement-based forecasts of profitability after, relative to prior to, mandatory IFRS adoption. We also predict that this relation is moderated by whether the country implemented

concurrent changes in financial reporting enforcement, as analysts are less likely to place more reliance on financial statements around mandatory IFRS adoption if there is no improvement in enforcement. This leads to our fourth set of hypotheses:

H4a: Analyst forecasts are more positively associated with financial statement-based forecasts after mandatory IFRS adoption.

H4b: The greater association between analyst forecasts and financial statement-based forecasts after mandatory IFRS adoption is conditional on concurrent changes in enforcement.

III. Method

Forecasting Approach

We construct financial statement-based forecasts following recommendations of financial statement analysis research (Fairfield et al. 2003; Nissim and Penman 2001; Fairfield and Yohn 2001; Fairfield et al. 1996) and textbooks (Penman 2012; Lundholm and Sloan 2006). Specifically, following Nissim and Penman (2001), in our year-ahead ROE forecasting model, we decompose current pre-tax profitability ($ROE_{i,t}$) into pre-tax return on net operating assets ($RNOA_{i,t-1}$), leverage ($LEV_{i,t-1}$), and net borrowing costs ($NBC_{i,t-1}$). In addition, Fairfield et al. (1996) demonstrate that both extraordinary items ($XI_{i,t-1}$) and special items ($SPI_{i,t-1}$) are less likely to recur in the future, and should therefore be separated from net income for forecasting purposes. Thus, we include the return on net operating assets from extraordinary items ($RNOAXI_{i,t-1}$) and the return on net operating assets from special items ($RNOASPI_{i,t-1}$) as separate predictors of pre-tax profitability. Correspondingly, pre-tax return on net operating assets is adjusted for extraordinary and special items to calculate pre-tax return on net operating assets before extraordinary and special items ($RNOABXISPI_{i,t-1}$).

Further, Fairfield et al. (2003) show that the change in net operating assets is informative about year-ahead profitability. Therefore, we include growth in net operating assets ($\Delta NOA_{i,t-1}$) as a predictor in the model. Finally, Fairfield and Yohn (2001) provide evidence that the change in asset turnover and the change in profit margin are incrementally useful for forecasting. Accordingly, we include the change in asset turnover ($\Delta ATO_{i,t-1}$) and the change in profit margin ($\Delta PM_{i,t-1}$) as predictors in the forecasting model. Our financial statement-based approach to forecasting profitability is estimated as follows:

$$ROE_{i,t} = \alpha_0 + \alpha_1 RNOABXISPI_{i,t-1} + \alpha_2 RNOAXI_{i,t-1} + \alpha_3 RNOASPI_{i,t-1} + \alpha_4 LEV_{i,t-1} + \alpha_5 NBC_{i,t-1} + \alpha_6 \Delta NOA_{i,t-1} + \alpha_7 \Delta ATO_{i,t-1} + \alpha_8 \Delta PM_{i,t-1} + \varepsilon_{i,t} \quad (1)$$

In order to control for inter-temporal instabilities likely to violate the assumption of constant parameters, we estimate the in-sample coefficients using rolling three-year regressions. Further, the rolling regressions are estimated country-by-country, within each industry, and separately for the pre- and post-IFRS adoption period.[8] All coefficients and the associated t-statistics from the rolling regressions are estimated in accordance with Fama and MacBeth (1973) and adjusted for cross-sectional correlation following the Newey and West (1987) approach.

Using the in-sample parameter estimates from model (1), we calculate out-of-sample forecasts of ROE for the pre- and the post-IFRS adoption period. The forecasts for the pre-IFRS adoption period are computed by applying in-sample coefficients derived from regression analyses for the years 1998 through 2000 (1999 through 2001; 2000 through 2002) to data from 2001 (2002; 2003) to compute out-of-sample forecasts of ROE in 2002 (2003; 2004). Correspondingly, to forecast ROE in the post-IFRS adoption period, the regression analyses use three years of data from 2006 through 2008 (2007 through 2009; 2008 through 2010) to derive in-sample coefficients that are applied to data from 2009 (2010; 2011) to compute out-of-sample forecasts of ROE in 2010 (2011; 2012).[9]

We do not report and discuss the cross-sectional means and t-statistics of the in-sample regression coefficients.[10] Instead, we evaluate the forecast accuracy of the model in out-of-sample tests. For that purpose, we calculate the financial statement-based forecast error as the absolute difference between the forecasted ROE and the actual ROE for the respective year.[11] Lower forecast errors suggest higher forecast accuracy.

[8] However, we pool data across industries for those industries with less than 25 firm-year observations. Pooling all country-specific data across industries does not qualitatively change the findings.

[9] We note that the post-IFRS adoption period includes the recession related to the financial crisis in 2008 which affected both the IFRS adopting countries and the US. We have excluded financial firms from the analysis so that firms most directly impacted by the financial crisis are not included in the analyses. In addition, we note that the inclusion of the recessionary period after 2008 is likely to bias against finding an improvement in financial statement-based forecasts after IFRS adoption. In addition, the univariate findings suggest an improvement in financial statement-based forecasts in the post- IFRS adoption for IFRS adopting firms and no significant change in the accuracy of financial statement-based forecasts for the US firms in the post period. These findings suggest that the recession related to the 2008 financial crisis is unlikely to drive the finding of an improvement in financial statement-based forecasts in the post-IFRS adoption period.

[10] However, the in-sample regression results are available from the authors upon request.

[11] Please note that our hypotheses focus on forecast accuracy which is captured by the absolute difference between the forecasted ROE and the actual ROE. Future research could examine whether mandatory IFRS adoption affected the bias in financial statement-based forecasts (i.e., the signed difference between the forecasted ROE and the actual ROE), and whether any change in bias is associated with the incentives prevalent in the country.

Regression Models

To test our first set of hypotheses, we specify our regressions as change models. For example, we subtract the pre-IFRS adoption analyst forecast error from the post-IFRS adoption analyst forecast error. Positive (negative) analyst forecast error changes represent improvements (reductions) in forecast accuracy around mandatory IFRS adoption. To control for confounding concurrent effects, we use firms from the US that used US GAAP throughout the sample period as a benchmark sample. Thus, any change in forecast accuracy in the US is likely to reflect the impact of concurrent economic changes not caused by mandatory IFRS adoption but likely to affect forecasting performance in the periods before and after mandatory IFRS adoption (Ahmed et al. 2013).[12]

Our research design to test whether the accuracy of analyst forecasts of profitability changes with mandatory IFRS adoption is specified as follows:

$$\Delta AFE_i = \beta_0 + \beta_1 IFRS_i + \beta_2 \Delta SIZE_i + \beta_3 \Delta LEV_i + \beta_4 \Delta LOSS_i + \beta_5 \Delta GAAP_i + \beta_6 \Delta GOV_i + \beta_7 \Delta GDP_i + \beta_8 \Delta FOLLOWING_i + \beta_9 \Delta HORIZON_i + \sum_{k=10}^{n} \beta_k INDUSTRY + \varepsilon_i \quad (2)$$

ΔAFE$_i$ is the change in analysts' average forecast error from the pre- to the post-IFRS adoption period for firm *i*, where the analyst forecast error is calculated as the absolute difference between the median analyst consensus forecasted ROE and the actual ROE.[13] In order to mitigate the effect of information leakage (Madura and Premti 2014) that is likely to reduce the association of analyst forecast errors with the forecast errors from our financial statement-based model, we use the earliest analyst consensus forecast provided by I/B/E/S for the respective fiscal year.[14] *IFRS*$_i$ is an indicator variable that equals one if the firm prepares its financial statements according to IFRS after mandatory IFRS adoption in 2005. The control variables are also specified as changes from the pre- to the post-IFRS adoption period and include the changes in firm size (*ΔSIZE*$_i$ – defined as the pre- vs. post-IFRS average natural log of total assets), leverage (*ΔLEV*$_i$ – defined as the pre- vs. post-IFRS

[12] We note that any improvements in financial reporting in the US from regulations such as the Sarbanes-Oxley Act biases against finding relative improvements in forecast accuracy from IFRS adoption.

[13] The median analyst consensus forecasted ROE is calculated as the median consensus earnings per share (as reported by the I/B/E/S database) times the number of shares outstanding and divided by the book value of equity. Our results remain qualitatively similar using the mean consensus forecasted ROE.

[14] In later analyses, we use other analyst consensus forecast specifications to assess the robustness of our results to the choice of forecast horizon. These specifications include the analyst consensus forecast that is calculated three months before fiscal year-end as well as the most recent analyst consensus forecast before fiscal year-end. The alternative specifications do not change our results qualitatively.

average net financial obligations divided by book value of equity), the number of loss years ($\Delta LOSS_i$ – defined as the pre- vs. post-IFRS number of times prior year's income was negative), the difference between IFRS and domestic GAAP ($\Delta GAAP_i$ – defined as the change in Bae et al.'s (2008) measure for accounting differences between IFRS and pre-existing GAAP), the governance quality of a country's institutional environment (ΔGOV_i – defined as the pre- vs. post-IFRS average of four indicators presented in Kaufman et al. (2009) which capture the public's perception with respect to the rule of law, control of corruption, government effectiveness, and regulatory quality), and GDP (ΔGDP_i – defined as the percentage change of a country's average yearly gross domestic product from the pre- to the post-IFRS period).[15] In addition, we include the change in analyst coverage ($\Delta FOLLOWING_i$ – defined as the pre- vs. post-IFRS average number of analysts following the firm), and the change in analyst forecast horizon ($\Delta HORIZON_i$ – defined as the pre- vs. post-IFRS average number of days between the analysts' consensus forecast's issue date and the fiscal year end). Finally, we include industry fixed effects (*INDUSTRY*) using two-digit GICS industry sector classifications. We cluster standard errors at the firm level to mitigate cross- correlation among firms.

Correspondingly, the model to test the consequences of mandatory IFRS adoption on the accuracy of financial statement-based forecasts of profitability is as follows:

$$\Delta FSFE_i = \beta_0 + \beta_1 IFRS_i + \beta_2 \Delta SIZE_i + \beta_3 \Delta LEV_i + \beta_4 \Delta LOSS_i + \beta_5 \Delta GAAP_i + \beta_6 \Delta GOV_i + \beta_7 \Delta GDP_i + \sum_{k=8}^{n} \beta_k INDUSTRY + \varepsilon_i \quad (3)$$

We define $\Delta FSFE_i$ as the change in the average financial statement-based forecast error from the pre- to the post-IFRS adoption period. In conjunction with equation (2), the additional control variables are the changes in firm size, leverage, the number of loss years, the number of differences between IFRS and domestic GAAP, the governance quality of the country's institutional environment, and GDP. Again, the model is estimated using industry fixed effects and standard errors clustered at the firm level.

To investigate whether the change in the accuracy of analyst forecasts and the financial statement-based forecasts around mandatory IFRS adoption are conditional on concurrent changes in enforcement (tests of *H2a* and *H2b*), we split the IFRS sample based on whether the country implemented concurrrent changes in enforcement following the

[15] The Kaufmann et al. (2009) study reports worldwide governance indicators for 212 countries which represent aggregates of hundreds of specific and disaggregated individual variables measuring various dimensions of governance, taken from 35 data sources provided by 33 different organizations. The data reflect the views on governance of public sector, private sector and non-government experts, as well as thousands of citizen and company survey respondents worldwide.

research strategy of Christensen et al. (2013).[16] That is, we distinguish between (1) countries that switched to IFRS and, at the same time, implemented substantive enforcement changes and (2) countries that switched to IFRS with no concurrent enforcement changes.[17] Accordingly, we combine the variables into the following regression models estimated at the firm-year level:

$$\Delta AFE_i = \beta_0 + \beta_1 IFRS\_ENF_i + \beta_2 IFRS\_nonENF_i + \beta_3 \Delta SIZE_i + \beta_4 \Delta LEV_i + \beta_5 \Delta LOSS_i + \beta_6 \Delta GAAP_i + \beta_7 \Delta GOV_i + \beta_8 \Delta GDP_i + \beta_9 \Delta FOLLOWING_i + \beta_{10} \Delta HORIZON_i + \sum_{k=11}^{n} \beta_k INDUSTRY + \varepsilon_i \quad (4)$$

$$\Delta FSFE_i = \beta_0 + \beta_1 IFRS\_ENF_i + \beta_2 IFRS\_nonENF_i + \beta_3 \Delta SIZE_i + \beta_4 \Delta LEV_i + \beta_5 \Delta LOSS_i + \beta_6 \Delta GAAP_i + \beta_7 \Delta GOV_i + \beta_8 \Delta GDP_i + \sum_{k=9}^{n} \beta_k INDUSTRY + \varepsilon_i \quad (5)$$

ΔAFE$_i$ and *ΔFSFE*$_i$ are defined as described above. *IFRS_ENF*$_i$ is an indicator variable that takes the value of one if the firm is from a country that bundled mandatory IFRS adoption with substantive changes in enforcement. *IFRS_nonENF*$_i$ is an indicator variable that takes the value of one if the firm is from a country that did not bundle mandatory IFRS adoption with substantive changes in enforcement. In conjunction with models (2) and (3), the additional control variables are changes in firm size, leverage, the number of loss years, the number of differences between IFRS and domestic GAAP, the governance quality of the country's institutional environment, GDP, analyst coverage, and analyst forecast horizon. Standard errors are clustered at the firm level.

Our model to test whether changes in analyst forecast accuracy are associated with changes in the accuracy of financial statement-based forecasts of profitability around mandatory IFRS adoption (tests of *H3*), is specified at the firm-level as follows:

[16] The identification strategy of Christensen et al. (2013) combines public sources such as annual reports of national securities regulators with a survey asking questions about changes in the enforcement of financial reporting. The authors sent the survey to national securities regulators, the technical partners at PricewaterhouseCoopers and academics.

[17] The relevant criteria for distinguishing between countries with substantive enforcement changes and without enforcement changes refers to the implementation of a proactive review process for financial statements (as the key criteria), new enforcement agencies, tightened penalties for violating accounting standards, and other enforcement changes. Please refer to Christensen et al. (2013) Appendix A for details on substantive enforcement changes for our sample countries.

$$\Delta AFE_i = \beta_0 + \beta_1 \Delta FSFE_i + \beta_2 \Delta FSFE_i * IFRS_i + \beta_3 \Delta SIZE_i + \beta_4 \Delta LEV_i + \beta_5 \Delta LOSS_i + \beta_6 \Delta GAAP_i + \beta_7 \Delta GOV_i + \beta_8 \Delta GDP_i + \beta_9 \Delta FOLLOWING_i + \beta_{10} \Delta HORIZON_i + \sum_{k=11}^{n} \beta_k INDUSTRY + \varepsilon_i \quad (6)$$

$$\Delta AFE_i = \beta_0 + \beta_1 \Delta FSFE_i + \beta_2 \Delta FSFE_i * IFRS\_ENF_i + \beta_3 \Delta FSFE_i * IFRS\_nonENF_i + \beta_4 \Delta SIZE_i + \beta_5 \Delta LEV_i + \beta_6 \Delta LOSS_i + \beta_7 \Delta GAAP_i + \beta_8 \Delta GOV_i + \beta_9 \Delta GDP_i + \beta_{10} \Delta FOLLOWING_i + \beta_{11} \Delta HORIZON_i + \sum_{k=12}^{n} \beta_k INDUSTRY + \varepsilon_i \quad (7)$$

As can be seen in equation (6), the change in analyst forecast errors (ΔAFE_i) is regressed on the change in financial statement-based forecast errors ($\Delta FSFE_i$), the IFRS indicator variable ($IFRS_i$), and the control variables from above. The coefficient β_1 captures whether the change in analyst forecast accuracy from the pre- to the post-IFRS adoption period is associated with the change in financial statement-based forecast errors for the US, as the US is the only non-IFRS adopting country. It follows that the interaction of $IFRS_i$ with $FSFE_i$ (i.e., β_2) captures the incremental relation between the change in financial statement-based forecast errors and the change of analyst forecast errors for those firms that adopted IFRS mandatorily.

In equation (7), we additionally distinguish between countries that switched to IFRS and concurrently implemented substantive enforcement changes ($IFRS\_ENF_i$) and countries that switched to IFRS with no concurrent enforcement changes ($IFRS\_nonENF_i$). Accordingly, the coefficient β_2 (β_3) captures the incremental effect of a change in financial statement-based forecast errors on the change in analyst forecast errors for firms in countries that bundled (did not bundle) mandatory IFRS adoption with changes in enforcement.

Our research design to test whether analyst forecasts are more positively associated with financial statement-based forecasts after mandatory IFRS adoption (tests of *H4a* and *H4b*), is specified at the firm-level as follows:

$$AFE_i = \beta_0 + \beta_1 FSFE_i + \beta_2 FSFE_i * POST_i + \beta_3 FSFE_i * POST * IFRS_i + \beta_4 SIZE_i + \beta_5 LEV_i + \beta_6 LOSS_i + \beta_7 GOV_i + \beta_8 GDP_i + \beta_9 FOLLOWING_i + \beta_{10} HORIZON_i + \sum_{k=11}^{n} \beta_k INDUSTRY + \varepsilon_i \quad (8)$$

$$AFE_i = \beta_0 + \beta_1 FSFE_i + \beta_2 FSFE_i * POST_i + \beta_3 FSFE_i * POST * IFRS\_ENF_i + \beta_4 FSAFE_i * POST * IFRS\_nonENF_i + \beta_5 SIZE_i + 6LEV_i + \beta_7 LOSS_i + \beta_8 GOV_i + \beta_9 GDP_i + \beta_{10} FOLLOWING_i + \beta_{11} HORIZON_i + \sum_{k=11}^{n} \beta_k INDUSTRY + \varepsilon_i \quad (9)$$

The coefficient of interest is β_3 in equation (8) and β_3 and β_4 in equation (9) as they capture whether the relation between analyst and financial statement-based forecast is more pronounced after mandatory IFRS adoption.

IV. EMPIRICAL ANALYSES

Sample and Descriptive Statistics

Table 1, Panel A, presents the variable definitions used in our study. Table 1, Panel B, describes the sample selection procedure for our estimation of in-sample coefficients, while Table 1, Panel C, presents the subsequent combination of our out-of-sample forecasts of ROE with data on analyst forecasts. We highlight the fact that all financial data are translated into US dollar amounts before applying the quantitative filters described below.[18]

[18] Balance sheet items are translated using spot exchange rates while income statement items are translated using the average exchange rates over the fiscal year.

Table 1 - Variable definitions and sample selection procedures

Panel A: Variable definitions

Variable	Description	Computation
CEQ_t	Common equity	
CHE_t	Cash and short-term investments	
DLC_t	Debt in current liabilities	
$DLTT_t$	Long-term debt	
DO_t	Discontinued operations	
DVP_t	Dividends preferred	
$DVPA_t$	Dividends preferred in arrears	
$IDIT_t$	Interest and related income	
$IVAO_t$	Other investments and advances	
NI_t	Net income	
$PSTK_t$	Preferred stock	
$REVT_t$	Revenues	
SPI_t	Special items	
TXT_t	Income taxes	
$TSTKP_t$	Preferred treasury stock	
$XINT_t$	Interest and related expense	
XI_t	Extraordinary items	
$NIBT_t$	Net income before taxes	$NI_t + TXT_t - DVP_t - DO_t$
CSE_t	Common shareholders' equity	$CEQ_t + TSTKP_t - DVPA_t$
FA_t	Financial assets	$CHE_t + IVAO_t$
FE_t	Financial expenses	$XINT + DVP$
FO_t	Financial obligations	$DLC_t + DLTT_t + PSTK_t - TSTKP_t + DVPA_t$
NFO_t	Net financial assets	$FO_t - FA_t$
NFE_t	Net financial expenses	$-(IDIT_t - XINT_t - DVP_t)$
NOA_t	Net operating assets	$FO_t - FA_t + CSE_t$
NOI_t	Net operating income	$NIBT_t + NFE_t$
$ANFO_t$	Average net financial obligations	$(NFO_t + NFO_{t-1}) / 2$
$ANOA_t$	Average net operating assets	$(NOA_t + NOA_{t-1}) / 2$
ATO_t	Asset turnover	$REVT_t / ANOA_t$
BVE_t	Average common shareholders' equity	$(CSE_t + CSE_{t-1}) / 2$
LEV_t	Leverage	$ANFO_t / BVE_t$
NBC_t	Net borrowing costs	$NFE_t / ANFO_t$
PM_t	Profit margin	$NOI_t / REVT_t$
ROE_t	Return on equity	$NIBT_t / BVE_t$
$RNOA_t$	Return on net operating assets	$NOI_t / ANOA_t$
$RNOABXISPI_t$	Return on net operating assets before extraordinary and special items	$(NOI_t + XI_t + SPI_t) / ANOA_t$
$RNOAXI_t$	Return on net operating assets from extraordinary items	$XI_t / ANOA_t$
$RNOASI_t$	Return on net operating assets from special items	$SPI_t / ANOA_t$
ΔNOA_t	Change in net operating assets	$(NOA_t - NOA_{t-1}) / NOA_{t-1}$
ΔATO_t	Change in asset turnover	$(ATO_t - ATO_{t-1}) / ATO_{t-1}$
ΔPM_t	Change in profit margin	$(PM_t - PM_{t-1}) / PM_{t-1}$
AF_t	Analysts' median consensus forecast ROE.	
AFE_t	Analysts' forecast error calculated as the absolute difference between the consensus forecast ROE and the actual ROE.	
FSF_t	Financial statement analysis-based forecast ROE (out-of-sample), estimated by using the in-sample parameter estimates from regression equation (1).	
$FSFE_t$	Financial statement analysis-based forecast error caclulated as the absolute difference between the forecast ROE and the actual ROE of the respective year.	
$FOLLOWING_t$	Number of analysts following the firm.	
$GAAP_t$	Bae et al. 2008 measure for accounting differences between IFRS and pre-existing GAAP.	
GDP_t	A country's yearly gross domestic product.	
GOV_t	average of four indicators presented in Kaufman et al. 2009 which capture the public's preception with respect to the rule of law, control of corruption, government effectiveness, and regulatory quality.	
$HORIZON_t$	Number of days between the analysts' consensus forecast's issue date and the fiscal year end.	
$IFRS_t$	Indicator variable for firms which prepare its financial statements according to IFRS after IFRS has become mandatory.	
$IFRS\_ENF_t$	Indicator variable for firms from countries that bundled mandatory IFRS adoption with substantive enforcement changes.	
$IFRS\_nonENF_t$	Indicator variable for firms from countries that did not bundle mandatory IFRS adoption with substantive enforcement changes.	
$INDUSTRY_t$	Industry fixed effects using two-digit GICS industry sector classifications.	
$LOSS_t$	Indicator variable if the prior year's negative income is negative.	
$SIZE_t$	Natural log of total assets.	

Variable definitions and sample selection procedures

Panel B: Construction of sample used to estimate in-sample coefficients

Firm-year observations between 1998 and 2012 with sufficient data to calculate independent and dependent variables	97,601
less Exclusions of firm-year observations characterized by:	
Financial industry classification or possessing segments in this industry	999
$ANOA_{t-1}$ less than $10 million	21,664
BVE_{t-1} less than $1 million	2,026
$ANFO_{t-1}$ less than $5 million	8,849
Absolute value of ROE_t or ROE_{t-1} greater than 1	4,098
NBC_{t-1} less than 0 or greater than 1	295
Percentage of ΔNOA_{t-1}, ΔBVE_{t-1}, or $\Delta SALES_{t-1}$ greater than 1	4,410
Country-specific observations for a fiscal year below 25	455
Firm-year observations used to estimate in-sample coefficients	54,805
Unique firms used to estimate in-sample coefficients	*10,039*

Panel C: Construction of sample used for main analyses

Number of out-of-sample forecasts of ROE (firm-year observations)	54,805
less Exclusions of firm-year observations characterized by:	
Missing data coverage by I/B/E/S	16,735
IFRS transition year 2005, as well as multiple GAAP years 2006 through 2009	22,348
Voluntary IFRS adopters	678
Missing firm data for the pre- or the post-IFRS adoption period	8,821
Extreme values for change variables (truncation at 5 and 95%)	1,091
Firm-year observations used in main analyses	5,132
Unique firms used in main analyses	*1,074*

Our initial sample is drawn from all 22 countries that mandatorily adopted IFRS in 2005 as well as the US as a control country.[19] We begin our sample selection procedure with 97,601 firm-year observations from 1998 through 2012 for which relevant financial information is available from the Compustat Global database for at least five consecutive years.[20] We exclude 999 firm-year observations that are classified as financial firms (SIC codes between 6000 and 6999) or possess segments in this industry. Further, we aggressively eliminate firms based on several criteria likely to introduce measurement error

[19] Please refer to Table 2 for an overview of firm-year observations across countries.
[20] A minimum of five consecutive years of historical data is required to perform out-of-sample forecasts based on rolling three-year regressions.

into our forecasting approach and in order to avoid the effect of small denominators.[21] Specifically, we delete firm-year observations with less than $10 million in *ANOA* (21,664 firm-year observations), $1 million in *BVE* (2,026 firm-year observations), and $5 million in *ANFO* (8,849 firm-year observations), respectively, in year t – 1. In addition, we drop 4,098 firm-year observations with absolute values of *ROE* greater than one for year t or t – 1, 295 firm-year observations with *NBC* of less than minus one or greater than one for year t – 1, and 4,410 firm-years with an increase in *NOA*, *BVE*, or *Sales* in year t – 1 of greater than 100 percent.[22] Finally, we exclude 455 firm-year observations with less than 25 country-specific observations in a fiscal year. These procedures result in a sample of 54,805 firm-year observations (10,039 firms) used to derive our in-sample coefficient estimates.

From the in-sample coefficient estimates, we predict ROE out-of-sample. For the out-of-sample analyses, we eliminate 16,735 firm-year observations for which the I/B/E/S database provides no data coverage. Furthermore, we remove observations in 2005 due to potential transition effects of mandatory IFRS adoption, and 2006 through 2009 because these years are used for estimating the in-sample coefficients in the rolling 3-year regressions. This results in a reduction of 22,348 firm-year observations. Accordingly, our pre-IFRS adoption period includes the years 2002, 2003, and 2004 while the post-IFRS adoption period consists of the years 2010, 2011, and 2012. In addition, we eliminate all firms that voluntarily adopted IFRS before 2005 (678 firm-year observations). In order to employ a constant sample, we select the group of firms that have data available in both the pre- and the post-IFRS adoption period. Thus, 8,821 firm-year observations were eliminated from the sample. As the change model specifications are subject to extreme values, we truncate the sample at 5% and 95% (1,091 firm-year observations).

[21] The elimination procedure generally follows Esplin et al. (2014).
[22] The exclusion of firm-years of high growth is intended to reduce the effect of acquisitions.

Table 2 - Sample composition by country, IFRS adoption and concurrent reporting enforcement changes

IFRS Adopting Countries	Firm-year observations	Unique firms	% of total unique firms
with concurrent changes to enforcement			
Finland	152	30	5.1%
Germany	216	51	8.7%
Netherlands	71	14	2.4%
Norway	75	14	2.4%
United Kingdom	557	124	21.2%
Subtotal	*1,071*	*233*	*39.8%*
without concurrent changes to enforcement			
Australia	220	52	8.9%
Austria	12	2	0.3%
Belgium	83	18	3.1%
Denmark	77	17	2.9%
France	279	60	10.3%
Greece	42	8	1.4%
Hong Kong	112	22	3.8%
Ireland	52	11	1.9%
Italy	199	38	6.5%
Philippines	30	8	1.4%
Poland	10	2	0.3%
Portugal	45	8	1.4%
Republic of Singapore	83	19	3.2%
Sweden	165	34	5.8%
Switzerland	57	12	2.1%
South Africa	85	21	3.6%
Spain	104	20	3.4%
Subtotal	*1,655*	*352*	*60.2%*
Total	2,726	585	100%

Control Country	Firm-year observations	Unique firms	% of total unique firms
United States	2,406	489	100%

Notes:
The sample comprises firm-year observations from up to 23 countries. We split the sample into two groups: (1) a treatment group (22 countries) that includes countries that mandate the adoption of IFRS reporting in 2005 and (2) a benchmark group that comprises firms reporting under U.S. GAAP (US firms only). We further subdivide the treatment group into countries that either experienced or did not experience a substantive change in enforcement around the mandatory IFRS adoption. We use the main binary coding indicator IFRS_ENF and IFRS_nonENF as suggested by Christensen et al. (2013) (see Table 1 Panel A).

The sample selection procedure described above yields a total of 5,132 firm-year observations or 1,074 unique firms. Table 2 presents a breakdown of the sample size by country-based IFRS adoption and on whether the country implemented concurrent enforcement changes. Our final sample includes 585 IFRS adopting firms (2,726 firm-year observations) from 22 countries and 489 firms (2,406 firm-year observations) from the US as the non-IFRS adopting control country.[23] Thereby, 233 firms (1,071 firm-year oberservations) are in countries that bundled mandatory IFRS adoption with substantive changes in enforcement, while 352 firms (1,655 firm-year observations) are from IFRS adopting countries with no concurrent enforcement changes. The majority of mandatory IFRS adopters are incorporated in Australia, Germany, Italy, Sweden, and the United Kingdom. The sample composition of mandatory IFRS adopters is generally consistent with Daske et al. (2008) and Horton et al. (2013).

Table 3 shows the descriptive statistics and correlations for the variables used in our main analyses. All continuous control variables are deflated by year-end total assets to avoid possible scale effects.[24] Table 3, Panel A, presents the descriptive statistics for the change variables and their respective level specifications. With respect to our main variables of interest, the mean (median) ΔAFE_i is 6.5% (1.1%), while the mean (median) $\Delta FSFE_i$ is 11.6% (1.1%). In Table 3, Panel B, we present the Spearman (Pearson) correlations below (above) the diagonal of the correlation matrix. We note that ΔAFE_i and $\Delta FSFE_i$ are positively and significantly correlated ($\rho_{Spearman}$ = 0.35; $\rho_{Pearson}$ = 0.30) while none of the other variables included simultaneously in the regression models are highly correlated. We also calculated the variance inflation factors (VIF) to verify that multicollinearity is not an issue.

[23] Profitability (in terms of return on equity) does not differ between the IFRS adopting firms and the US non-IFRS adopting control firms in the pre-IFRS adoption period or in the post-IFRS adoption period.
[24] Deflating by beginning total assets reduces our sample size but does not change our results qualitatively.

Table 3 - Descriptive statistics and correlation matrix
Panel A: Descriptive statistics

	Mean	Median	Std. Dev.	First Quartile	Third Quartile	Min.	Max.
$AFE_{i,t}$	0.448	0.161	0.953	0.062	0.417	0.000	19.778
ΔAFE_{i}	0.065	0.011	0.706	-0.129	0.222	-2.706	2.969
$FSFE_{i,t}$	0.930	0.530	1.531	0.296	0.926	0.000	23.282
$\Delta FSFE_{i}$	0.116	0.011	1.186	-0.320	0.430	-3.473	5.854
$FOLLOWING_{i,t}$	8.590	6.000	7.259	3.000	13.000	1.000	47.000
$\Delta FOLLOWING_{i}$	-2.461	-1.667	5.069	-5.333	0.333	-22.500	16.333
$GAAP_{i,t}$	2.841	0.000	4.203	0.000	4.000	0.000	17.000
$\Delta GAAP_{i}$	4.044	1.000	5.455	0.000	10.000	0.000	17.000
$GDP_{i,t}$	7.059	2.647	6.387	0.529	11.590	0.086	15.579
ΔGDP_{i}	0.463	0.344	0.261	0.344	0.498	0.266	1.755
$GOV_{i,t}$	1.528	1.624	0.412	1.457	1.720	-0.411	2.149
ΔGOV_{i}	0.103	0.189	0.199	0.025	0.206	-1.463	0.444
$HORIZON_{i,t}$	340.722	349.000	38.237	341.000	357.000	35.000	365.000
$\Delta HORIZON_{i}$	4.065	0.083	42.224	-7.333	7.000	-131.833	259.000
$IFRS_{i}$	0.270	0.000	0.444	0.000	1.000	0.000	1.000
$IFRS_{i,t}$	0.545	1.000	0.498	0.000	1.000	0.000	1.000
$IFRS\_ENF_{i}$	0.209	0.000	0.406	0.000	0.000	0.000	1.000
$IFRS\_ENF_{i,t}$	0.217	0.000	0.412	0.000	0.000	0.000	1.000
$IFRS\_nonENF_{i}$	0.322	0.000	0.467	0.000	1.000	0.000	1.000
$IFRS\_nonENF_{i,t}$	0.328	0.000	0.470	0.000	1.000	0.000	1.000
$LEV_{i,t}$	0.332	0.226	0.762	-0.165	0.623	-0.845	4.855
ΔLEV_{i}	0.010	0.024	0.631	-0.221	0.300	-3.721	2.138
$LOSS_{i,t}$	0.153	0.000	0.360	0.000	0.000	0.000	1.000
$\Delta LOSS_{i}$	0.006	0.000	0.383	0.000	0.000	-1.000	1.000
$SIZE_{i,t}$	7.020	6.901	1.589	5.865	8.057	2.481	12.348
$\Delta SIZE_{i}$	-0.639	-0.611	0.632	-1.008	-0.218	-2.655	1.707

Descriptive statistics and correlation matrix

Panel B: Correlation matrix (for change variables used in main analyses)

	ΔAFE_i	$\Delta FSFE_i$	$\Delta FOLLOWING_i$	$\Delta GAAP_i$	ΔGDP_i	ΔGOV_i	$\Delta HORIZON_i$	$IFRS_i$	$IFRS\_ENF_i$	$IFRS\_nonENF_i$	ΔLEV_i	$\Delta LOSS_i$	$\Delta SIZE_i$
ΔAFE_i		0.30	***-0.02***	***-0.04***	***0.00***	***-0.03***	0.07	***0.00***	0.06	-0.05	0.12	0.26	***0.00***
$\Delta FSFE_i$	0.35		***0.01***	0.08	***0.04***	***0.03***	***0.04***	0.09	***0.01***	0.09	***0.02***	0.24	***0.01***
$\Delta FOLLOWING_i$	-0.06	***0.01***		0.14	0.20	-0.10	***-0.05***	0.06	-0.16	0.20	***-0.01***	-0.07	0.30
$\Delta GAAP_i$	***-0.05***	0.12	0.11		0.27	***-0.03***	***0.00***	0.68	0.14	0.59	-0.06	***-0.03***	-0.08
ΔGDP_i	-0.06	0.09	0.27	0.57		-0.15	***0.05***	0.42	-0.12	0.55	***-0.03***	***0.02***	-0.19
ΔGOV_i	***0.02***	***-0.02***	-0.11	-0.25	-0.37		-0.10	-0.07	***0.04***	-0.11	-0.09	***0.02***	***0.03***
$\Delta HORIZON_i$	0.06	***0.04***	***-0.05***	***0.01***	***-0.01***	***0.03***		0.08	0.06	***0.03***	***0.01***	0.06	-0.09
$IFRS_i$	***0.00***	0.13	0.07	0.86	0.52	-0.33	0.03		0.48	0.64	-0.06	***-0.03***	-0.13
$IFRS\_ENF_i$	0.07	***0.02***	-0.16	0.34	-0.24	-0.12	0.06	0.48		-0.37	***0.00***	***0.02***	***0.03***
$IFRS\_nonENF_i$	-0.06	0.12	0.22	0.61	0.77	-0.24	***-0.02***	0.64	-0.37		-0.06	-0.05	-0.17
ΔLEV_i	0.10	***0.02***	***-0.02***	-0.06	***-0.04***	-0.07	***-0.02***	-0.08	***-0.03***	-0.06		0.15	0.20
$\Delta LOSS_i$	0.31	0.27	-0.08	***-0.04***	***-0.02***	***0.03***	***0.02***	***-0.03***	***0.01***	***-0.05***	0.11		-0.12
$\Delta SIZE_i$	***-0.02***	***-0.01***	0.32	-0.09	-0.18	***0.05***	-0.06	-0.13	***0.02***	-0.16	0.20	-0.10	1.00

Notes:

This table reports descriptive statistics and correlations for the variables used in our analyses. See Table 1 Panel A, for variable definitions. Data are firm, or respectively, firm-year observations from the pre-IFRS adoption period 2002 through 2004 and the post-IFRS adoption period 2010 through 2012. Number of firm-year observations is 5,132 (1,074 unique firms). In Panel B, Spearman (Pearson) correlations are presented below (above) the diagonal. All correlations in bold and italic are not significant at and below the 10% level.

Difference-in-Differences Analysis

To test our three sets of hypotheses we first investigate whether the adoption of IFRS is associated with a change in analyst forecast accuracy and/or the accuracy of the financial statement-based model for the firms in our sample. Thus, we begin our analysis with univariate comparisons of the mean $AFE_{i,t}$ and $FSFE_{i,t}$ from the pre- to the post-IFRS adoption period using a difference-in-differences design. This procedure accounts for unobserved differences between treatment and control firms while adjusting for observed changes in the treatment firms by incorporating concurrent changes in the control firms (Daske et al. 2008). Specifically, we calculate the difference in the mean forecast errors between mandatory IFRS adopters and the US control group and then compare the relative changes over time. Tests of means (medians) are computed using t-tests (Wilcoxon Signed Ranks tests) of the forecast errors.

The upper quadrants of Table 4 report the mean values of $AFE_{i,t}$ and $FSFE_{i,t}$ for the mandatory IFRS adopters ($IFRS_{i,t}$ = 1) and the US control group ($IFRS_{i,t}$ = 0) for the fiscal years 2002 through 2004, and respectively, 2010 through 2012. As can be seen here, the mean $AFE_{i,t}$ decreases for both the mandatory IFRS adopters (by 6.77%) as well as the US control firms (by 6.26%). Thus, the significant difference in the analyst forecast error between the IFRS/non-IFRS adopting firms in the pre-IFRS adoption period (52.9% for $IFRS_{i,t}$ = 1; 44.93% for $IFRS_{i,t}$ = 0) remains in the post-IFRS adoption period (46.15% for $IFRS_{i,t}$ = 1; 38.67% for $IFRS_{i,t}$ = 0).

In contrast, the mean pre-IFRS adoption financial statement-based forecast error is significantly higher for mandatory IFRS adopters in comparison to the US control group, but this gap decreases and becomes insignificant in the post-IFRS adoption period. For instance, the mean $FSFE_{i,t}$ for mandatory IFRS adopters is 109.36% in the pre-IFRS adoption period and decreases to 87.85% in the post-IFRS adoption period. Over the same period, however, the US benchmark firms experience a slight increase in the mean $FSFE_{i,t}$ from 84.45% to 84.67%.

The lower quadrants of Table 4 present the mean values of $AFE_{i,t}$ and $FSFE_{i,t}$, for the fiscal years 2002 through 2004, and respectively, 2010 through 2012 for firms from countries that bundled mandatory IFRS adoption with substantive changes in enforcement ($IFRS\_ENF_{i,t}$ = 1), for firms that did not bundle mandatory IFRS adoption with substantive changes in enforcement ($IFRS\_nonENF_{i,t}$ = 1), and for firms from the US control group ($IFRS_{i,t}$ = 0). The univariate comparisons of the mean $AFE_{i,t}$ show that the analyst forecast error significantly decreased for mandatory IFRS adopters from countries with substantive

changes in enforcement (from 50.93% in the pre-IFRS adoption period to 36.34% in the post-IFRS adoption period), while the analyst forecast error did not change significantly for mandatory IFRS adopters from countries without substantive changes in enforcement (from 54.23% in the pre-IFRS adoption period to 52.64% in the post-IFRS adoption period). This decrease for mandatory IFRS adopters with substantive changes in enforcement is significantly larger than the decrease in the mean $AFE_{i,t}$ for the US control firms.

Again, the mean pre-IFRS adoption financial statement-based forecast error is significantly higher for firms from IFRS adopting countries with concurrent changes in enforcement as well as for firms from IFRS adopting countries without concurrent changes in enforcement. In the post-IFRS adoption period these gaps decrease and become insignificant. That is, the mean $FSFE_{i,t}$ for mandatory IFRS adopters with substantive changes in enforcement (without substantive changes in enforcement) is 99.99% (115.56%) in the pre-IFRS adoption period and decreases to 85.52% (89.38%) in the post-IFRS adoption period, while the US benchmark firms experience a slight increase in the mean $FSFE_{i,t}$. We find no significant difference in the pre-IFRS nor in the post-IFRS adoption financial statement-based forecast accuracy for firms from countries that bundled mandatory IFRS adoption with substantive changes in enforcement versus firms from countries that did not bundle mandatory IFRS adoption with substantive changes in enforcement. We investigate whether these preliminary findings hold when controlling for changes in firm and country characteristics in the regression analyses below.

Table 4 - Difference-in-differences analysis of changes in forecast accuracy upon mandatory IFRS adoption

mean AFE $_{i,t}$		Pre-IFRS (years 2002-2004) *(a)*	Post-IFRS (years 2010-2012) *(b)*	*(a) - (b)*
$IFRS_{i,t} = 1$	(i)	0.529	0.4615	0.0677 **/†††
$IFRS_{i,t} = 0$	(ii)	0.4493	0.3867	0.0626 **/†††
	(i) - (ii)	0.0799 */†††	0.0748 */†††	0.0051

mean FSFE $_{i,t}$		Pre-IFRS (years 2002-2004) *(a)*	Post-IFRS (years 2010-2012) *(b)*	*(a) - (b)*
$IFRS_{i,t} = 1$	*(i)*	1.0936	0.8785	0.2151 ***/†††
$IFRS_{i,t} = 0$	*(ii)*	0.8445	0.8467	-0.0022 †††
	(i) - (ii)	0.2491 ***/†††	0.0318 ††	0.2173 ***/†††

mean AFE $_{i,t}$		Pre-IFRS (years 2002-2004) *(a)*	Post-IFRS (years 2010-2012) *(b)*	*(a) - (b)*
$IFRS\_ENF_{i,t} = 1$	*(i)*	0.5093	0.3634	0.1459 ***/†††
$IFRS\_nonENF_{i,t} = 1$	*(ii)*	0.5423	0.5264	0.0159
$IFRS_{i} = 0$	*(iii)*	0.4493	0.3867	0.0626 **/†††
	(i) - (ii)	-0.033	-0.163 ***/†	0.13 **/†††
	(i) - (iii)	0.060 †††	-0.0233	0.0833 †
	(ii) - (iii)	0.093 */†††	0.1397 ***/†††	-0.0467

mean FSFE $_{i,t}$		Pre-IFRS (years 2002-2004) *(a)*	Post-IFRS (years 2010-2012) *(b)*	*(a) - (b)*
$IFRS\_ENF_{i,t} = 1$	*(i)*	0.9999	0.8552	0.1447 **/†
$IFRS\_nonENF_{i,t} = 1$	*(ii)*	1.1556	0.8938	0.2618 ***/†††
$IFRS_{i} = 0$	*(iii)*	0.8445	0.8467	-0.0022 †††
	(i) - (ii)	-0.1557 †	-0.0386	-0.1171
	(i) - (iii)	0.155 *	0.0085 †	0.1469 **/†††
	(ii) - (iii)	0.3111 ***/†††	0.0471 †	0.264 ***/†††

Notes:

The difference-in-difference analysis compares the treatment group of mandatory IFRS adopters against the benchmark group that reports under U.S. GAAP during the entire sample period. The entire sample comprises 5,132 firm-year observations and 1,074 unique firms. The pre-IFRS adoption period includes firm-year observations between 2002 and 2004 before IFRS became mandatory for countries in our sample on December 31, 2005. The post-IFRS period includes firm-year observations from 2010 through 2012. We only report companies with observations available in both periods, holding the sample period constant. The table presents mean values of analysts' absolute forecast errors as well as of forecast errors from the financial statement-based model (see Table 1 Panel A for variable definitions). The first difference-in-difference analysis splits forecast errors from both variables of interest, AFE and FSFE, into IFRS adopters (585 unique firms) versus non-IFRS adopters (489 unique firms). The second difference-in-difference analysis further partitions IFRS adopters into countries where either changes in enforcements occurred (233 unique firms) or did not occur (352 unique firms) during the IFRS adoption period. *, **, *** indicate statistical significance of differences in means from two-tailed t-tests at the 10%, 5%, and 1% levels, respectively. †, † †, † † † indicate statistical significance of differences in medians at the 10%, 5%, and 1% levels, respectively, based on Wilcoxon Signed Rank tests.

Analysis of Changes in Forecast Accuracy around Mandatory IFRS Adoption

Table 5 presents the results for our change model equations (2) and (3) in which we examine the consequences of mandatory IFRS adoption on analyst forecast errors and financial statement-based forecast errors (tests of *H1a* and *H1b*). We find a significant improvement in analyst forecast accuracy from the pre- to the post-IFRS adoption period (column 1). Correspondingly, we find that the forecast accuracy of the financial statement-based model (column 2) significantly improves after mandatory IFRS adoption relative to firms that do not adopt IFRS.[1] This suggests that both analyst and financial statement-based forecasts of profitability are more accurate following mandatory IFRS adoption.

The results for our control variables indicate that a decrease in leverage and in the average number of loss years positively affects analyst forecast accuracy. Further, a decrease in firm size and in the number of loss years positively affects the accuracy of the financial statement-based model.

[1] The change in forecast error is calculated as the difference between the mean pre-IFRS and the mean post-IFRS adoption period forecast error. Thus, a positive value implies an improvement in forecast accuracy (i.e., a decrease in the forecast error). Accordingly, a positive IFRS coefficient in the regression model documents an improvement in forecast accuracy after mandatory IFRS adoption.

Table 5 - Analysis of changes in forecast accuracy upon mandatory IFRS adoption

Dependent Variable	ΔAFE_i		$\Delta FSFE_i$	
Independent Variables	Coefficient	t-statistics	Coefficient	t-statistics
Intercept	-0.03844	-0.32	0.37313	1.60
$IFRS_i$	**0.08969** *	**1.67**	**0.22554** **	**2.27**
$\Delta SIZE_i$	0.03713	0.93	0.06921 **	2.14
ΔLEV_i	0.09217 **	2.39	0.05405	-1.02
$\Delta LOSS_i$	0.43989 ***	6.40	0.13437 ***	5.88
$\Delta GAAP_i$	-0.00822	-1.62	0.00939	0.75
ΔGOV_i	-0.09972	-0.83	0.18015	0.57
ΔGDP_i	-0.02805	-0.32	0.11401	-0.11
$\Delta FOLLOWING_i$	-0.00059	-0.17		
$\Delta HORIZON_i$	0.00087	1.59		
Industry fixed effects	yes		yes	
Firms	1,074		1,074	
Adjusted R^2	0.0761		0.0664	

Notes:
This table presents the analysis of determinants of changes (improvements) in forecast accuracy of analysts (column 1) and the financial statement-based forecast model expressed in equation (1) (column 2) around mandatory IFRS adoption. The sample comprises 1,074 unique firms. See Table 1, Panel A, for variable definitions. The dummy variable IFRS takes the value of one if a firm prepares its financial statements according to IFRS after IFRS has become mandatory after 2005, and zero otherwise. The regression is estimated with industry fixed effects using two-digit GICS industry sector classifications (not reported). We report t-statistics based on robust standard errors clustered by firm. *, **, and *** indicate significance at the 10, 5, and 1 % levels, respectively.

Analysis of Concurrent Changes in Enforcement

The results for our change model equations (4) and (5), in which we examine the change in the accuracy of analyst forecasts and financial statement-based forecasts of profitability around mandatory IFRS adoption conditional on concurrent changes in enforcement (tests of *H2a* and *H2b*), are presented in Table 6. As described above, we include IFRS indicator variables which capture concurrent changes in enforcement following Christensen et al. (2013): we distinguish between IFRS adopting countries that implemented concurrent substantive enforcement changes ($IFRS\_ENF_i$), and those that did not implement

concurrent enforcement changes (*IFRS_nonENF*$_i$). As can be seen in column 1 of Table 6, only *IFRS_ENF*$_i$ is positively and significantly associated with the improvement in analyst forecast accuracy. *IFRS_nonENF*$_i$ is insignificant. This suggests that analyst forecast accuracy improves only for firms from countries that bundled mandatory IFRS adoption with substantive changes to reporting enforcement. However, and as shown in column 2 of Table 6, both *IFRS_ENF*$_i$ and *IFRS_nonENF*$_i$ are positive and significant indicating that the accuracy of financial statement-based forecasts improve for IFRS adopting countries whether or not there was a concurrent change in enforcement.

The results with respect to our control variables are generally consistent with Table 5. That is, a decrease in leverage and in the number of loss years positively affects analyst forecast accuracy. Also, a decrease in firm size and the number of loss years positively affects the accuracy of financial statement-based forecasts.

Table 6 - Analysis of changes in forecast accuracy upon mandatory IFRS adoption and the influence of concurrent changes to reporting enforcement

Dependent Variable	***ΔAFE*** $_i$		***ΔFSFE*** $_i$	
Independent Variables	Coefficient	t-statistics	Coefficient	t-statistics
Intercept	-0.05689	-0.46	0.41982	1.79
IFRS_ENF $_i$	**0.11607** **	**2.02**	**0.17351** *	**1.66**
IFRS_nonENF $_i$	**0.01971**	**0.27**	**0.37438** ***	**2.70**
ΔSIZE $_i$	0.03107	0.78	0.15515 **	2.25
ΔLEV $_i$	0.09168 **	2.38	-0.05325	-0.99
ΔLOSS $_i$	0.43617 ***	6.32	0.79875 ***	5.96
ΔGAAP $_i$	-0.00592	-1.20	0.00180	0.19
ΔGOV $_i$	-0.10716	-0.88	0.12070	0.67
ΔGDP $_i$	0.02516	0.25	-0.13444	-0.96
ΔFOLLOWING $_i$	0.00042	0.11		
ΔHORIZON $_i$	0.00085	1.55		
Industry fixed effects	yes		yes	
Firms	1,074		1,074	
Adjusted R^2	0.0770		0.0683	

Notes:
This table uses the same data set, dependent variables, and independent variables as described in Table 5. However, we further enhance the analyses by dividing firm-year observations reporting under IFRS into country-observations that either experienced (IFRS_ENF) or did not experience (IFRS_nonENF) subtantive enforcement changes around the mandatory adoption of IFRS. See Table 1 Panel A for variable definitions. The regression is estimated with industry fixed effects using two-digit GICS industy classifications (not reported). We report t-statistics based on robust standard errors clustered by firm. *, **, and *** indicate significance at the 10, 5, and 1 % levels, respectively.

Analysis of Changes in Analyst and Financial Statements-Based Forecast Accuracy

Table 7 reports the results for change model equations (6) and (7) in which we test whether changes in analyst forecast accuracy are associated with the changes in the accuracy of the financial statement-based model around mandatory IFRS adoption (tests of *H3*). In column 1 of Table 7, we find a positive and significant coefficient on the change in the financial statement-based accuracy, suggesting a general positive association between analyst forecast accuracy and the forecast accuracy of the financial statement-based model. The results in column 2 of Table 7 suggests that this association does not differ for mandatory IFRS adopters relative to firms that do not adopt IFRS. The coefficient on $\Delta FSFE_i$ * $IFRS_i$ is insignificant. Also, column 3 of Table 7 shows that current changes in reporting enforcement do not affect this relation as the coefficients on $\Delta FSFE_i$ * $IFRS\_ENF_i$ and $\Delta FSFE_i$ * $IFRS\_nonENF_i$ are again both insignificant. In summary, we find a positive relation between the accuracy of analyst forecasts and the accuracy of financial statement-based forecasts.

Table 7 - Analysis of analysts' incorporation of changes in financial statement-based forecast accuracy upon mandatory IFRS adoption and the influence of concurrent changes to reporting enforcement

Dependent Variable	ΔAFE_i		ΔAFE_i		ΔAFE_i	
Independent Variables	Coefficient	t-statistics	Coefficient	t-statistics	Coefficient	t-statistics
Intercept	-0.09938	-0.75	-0.09575	-0.72	-0.09823	-0.76
$\Delta FSFE_i$	**0.15148** ***	**5.32**	**0.15041** ***	**5.27**	**0.17935** ***	**3.87**
$\Delta FSFE_i$ * $IFRS_i$			**0.05695**	**1.12**		
$\Delta FSFE_i$ * $IFRS\_ENF_i$					**-0.00587**	**-0.09**
$\Delta FSFE_i$ * $IFRS\_nonENF_i$					**-0.06003**	**-0.93**
$\Delta SIZE_i$	0.01330	0.34	0.01453	0.37	0.01241	0.32
ΔLEV_i	0.09956 **	2.54	0.10039 **	2.56	0.10127 ***	2.60
$\Delta LOSS_i$	0.32012 ***	4.58	0.32184 ***	4.61	0.30967 ***	4.33
$\Delta GAAP_i$	-0.00624	-1.47	-0.00935 *	-1.91	-0.00565	-1.32
ΔGOV_i	-0.11799	-0.94	-0.11765	-0.94	-0.11322	-0.90
ΔGDP_i	0.00112	0.01	-0.02608	-0.32	0.00828	0.11
$\Delta FOLLOWING_i$	-0.00104	-0.32	-0.00067	-0.20	-0.00111	-0.34
$\Delta HORIZON_i$	0.00081	1.53	0.00076	1.45	0.00085	1.64
Industry fixed effects	yes		yes		yes	
Firms	1,074		1,074		1,074	
Adjusted R^2	0.1351		0.1350		0.1357	

Notes:

This table presents regression analyses examining the determinants of changes in analysts' absolute forecast errors around the mandatory adoption of IFRS. See Table 1 Panel A for variable definitions. The sample comprises 5,132 firm-year observations and 1,074 unique firms. We report t-statistics based on robust standard errors clustered by firm. *, **, and *** indicate significance at the 10, 5, and 1 % levels, respectively.

Analysis of Analysts' Reliance on Financial Statement-Based Forecasts

Table 8 reports our results for model equations (8) and (9) in which we test whether analyst forecasts have a greater association with financial statement-based forecasts following mandatory IFRS adoption and/or whether concurrent changes in reporting enforcement affect this relation (tests of *H4a* and *H4b*).[2] In column 1 of Table 8, we find a positive and significant coefficient on *FSFE*, suggesting a general reliance by analysts on the financial statement-based model. However, as indicated by column 2 of Table 8, this empirical association becomes weaker for mandatory IFRS adopters relative to firms that do not adopt IFRS. The coefficient on $FSFE_i$ * *POST* * $IFRS_i$ is negative and significant. However, if we distinguish between countries with and without concurrent changes in

[2] Please note that the sample composition changes for these analyses as we use firm data before the truncation of extreme values for change variables (see Table 1 Panel C). We then truncate AFE_t and $FSFE_t$ for the regression analyses at the 1st and 99th percentiles. This results in 5,538 firm-year observations from 1,253 unique firms. Our results remain qualitatively similar using the same sample composition as for the change model specifications.

enforcement, we document in column 3 of Table 8 that analysts do not place less weight on the financial statement-based model after mandatory IFRS adoption for firms in countries with concurrent enforcement changes. The coefficient on $FSFE_i$ * $POST$ * $IFRS\_ENF_i$ is insignificant. Interestingly, the coefficient on $FSFE_i$ * $POST$ * $IFRS\_nonENF_i$ is negative and significant. This suggests that analysts place less reliance on financial statement-based forecasts after mandatory IFRS adoption only for firms in countries without concurrent changes in enforcement.

Table 8 - Analysis of analysts' reliance on financial statement-based forecasts around mandatory IFRS adoption

Dependent Variable	***AFE*** $_i$		***AFE*** $_i$		***AFE*** $_i$	
Independent Variables	Coefficient	t-statistics	Coefficient	t-statistics	Coefficient	t-statistics
Intercept	0.01713	1.55	0.01753	1.53	0.01828	1.56
FSFE $_i$	**0.12012** ***	**4.42**	**0.11559** ***	**4.60**	**0.11583** ***	**4.63**
FSFE $_i$ **** POST*** $_t$			**0.05157** **	**2.10**	**0.05290** **	**2.18**
FSFE $_i$ **** POST*** $_t$ **** IFRS*** $_i$			**-0.08339** *	**-1.72**		
FSFE $_i$ **** POST*** $_t$ **** IFRS_ENF*** $_i$					**0.05776**	**0.93**
FSFE $_i$ **** POST*** $_t$ **** IFRS_nonENF*** $_i$					**-0.16184** ***	**-3.15**
$SIZE_{i,t}$	-0.00306 **	-2.23	-0.00299 **	-2.19	-0.00265 **	-2.10
$LEV_{i,t}$	-0.00117	-0.88	-0.00119	-0.88	-0.00135	-1.00
$LOSS_{i,t}$	0.01506 ***	7.77	0.01514 ***	7.80	0.01535 ***	7.78
$GOV_{i,t}$	0.00807 ***	4.70	0.00830 ***	4.51	0.00685 ***	3.46
$GDP_{i,t}$	-0.00120 ***	-6.85	-0.00142 ***	-5.64	-0.00146 ***	-5.71
$FOLLOWING_{i,t}$	-0.00005	-0.12	-0.00007	-0.17	-0.00014	-0.36
$HORIZON_{i,t}$	0.00008 ***	4.81	0.00008 ***	4.77	0.00007 ***	4.62
Industry fixed effects	yes		yes		yes	
Firm-year observations	5,547		5,547		5,547	
Firms	1,252		1,252		1,252	
Adjusted R^2	0.0747		0.0755		0.0802	

Notes:
This table presents regression analyses explaining analyst forecast errors, AFE. See Table 1 Panel A for variable definitions. We use data before the truncation of extreme values for change variables (see Table 1 Panel C). We then truncate AFEt and FSFEt for the regression analyses at the 1st and 99th percentiles. This ends in 5,547 firm-year observations from 1,252 unique firms. The regression is estimated with industry fixed effects using two-digit GICS classifications (not reported). We report t-statistics based on robust two-way clustered standard errors by firm and year. *, **, and *** indicate significance at the 10, 5, and 1 % levels, respectively.

We find that financial statement-based forecast accuracy improves following mandatory IFRS adoption in countries with and without concurrent changes in enforcement. We also find that analysts place the same weight on financial statement–based forecasts following mandatory IFRS adoption in countries with concurrent enforcement changes and place less weight in countries without concurrent enforcement changes. This combination of

findings raises the question as to whether analyst forecasts might be improved by incorporating the information provided by the financial statement-based forecasts. In other words, would analysts benefit from placing more weight on financial statement-based forecasts after mandatory IFRS adoption? We address this additional research question by formulating the following two regression models which are based on the work of Dreman and Berry (1995):

$$ROE_{i,t} = \beta_0 + \beta_1 AF_{i,t} + \beta_2(FSF_{i,t} - AF_{i,t}) + \beta_3((FSF_{i,t} - AF_{i,t}) * IFRS_{i,t}) + \beta_4 SIZE_{i,t} + \beta_5 LEV_{i,t} + \beta_6 LOSS_{i,t} + \beta_7 GAAP_{i,t} + \beta_8 GOV_{i,t} + \beta_9 GDP_{i,t} + \beta_{10} FOLLOWING_{i,t} + \beta_{11} HORIZON_{i,t} + \sum_{k=12}^{n} \beta_k INDUSTRY + \varepsilon_{i,t} \quad (10)$$

$$ROE_{i,t} = \beta_0 + \beta_1 AF_{i,t} + \beta_2(FSF_{i,t} - AF_{i,t}) + \beta_3((FSF_{i,t} - AF_{i,t}) * IFRS\_ENF_{i,t}) + \beta_4((FSAF_{i,t} - AF_{i,t}) * IFRS\_nonENF_{i,t}) + \beta_5 SIZE_{i,t} + \beta_6 LEV_{i,t} + \beta_7 LOSS_{i,t} + \beta_8 GAAP_{i,t} + \beta_9 GOV_{i,t} + \beta_{10} GDP_{i,t} + \beta_{11} FOLLOWING_{i,t} + \beta_{12} HORIZON_{i,t} + \sum_{k=13}^{n} \beta_k INDUSTRY + \varepsilon_{i,t} \quad (11)$$

The two models presented in equation (10) and (11) regress actual profitability as measured by $ROE_{i,t}$ on the analyst forecast.[3] If analysts are excellent forecasters at the consensus level, one would expect the β_1 coefficient to be equal to 1 and the other coefficients to be zero. As a consequence, any deviation from these expectations can provide insight into whether information is missed by the analysts. Accordingly, we include the difference between the financial statement-based forecast of ROE and the analyst forecast of ROE $(FSF_{i,t} - AF_{i,t})$ to examine whether financial statement-based forecasts provide incremental information over analyst forecasts for explaining actual profitability.

As can be seen in column 1 of Table 9, the coefficient of $AF_{i,t}$ is positive and significant, but less than 1. $(FSF_{i,t} - AF_{i,t})$ is also positively and significantly associated with $ROE_{i,t}$, indicating that financial statement-based forecasts provide incremental information over analyst forecasts for explaining actual profitability. In column 2 of Table 9, we find that the coefficient on $((FSF_{i,t} - AF_{i,t}) * POST * IFRS_{i,t})$ is positive and significant, which suggests that financial statement-based forecasts are incrementally informative over analyst forecasts for explaining future ROE for firms in countries that mandatorily adopted IFRS. Finally, the regression results presented in column 3 reveal that the incremental usefulness of financial

[3] Please note that for this part of our analysis $ROE_{i,t}$ is calculated as the actual earnings per share (as reported by the I/B/E/S database) times the number of shares outstanding and divided by the book value of equity. This should bias against finding incremental improvement to analyst forecasts by incorporating the information provided by the financial statement-based forecasts due to the fact that I/B/E/S does not provide detailed explanations with respect to which items are eliminated from the actual as well as the median consensus earnings per share number. Our results remain qualitatively similar using the mean consensus forecasted ROE.

statement-based forecasts over analyst forecasts following mandatory IFRS adoption is not conditional on whether or not the adopting country bundled the adoption of IFRS with concurrent changes to enforcement.

Table 9 - Analyis of the incremental explanatory power of financial-statement based forecasts over analysts' forecasts to explain actual ROE

Dependent Variable	***ROE*** $_{i,t}$		***ROE*** $_{i,t}$		***ROE*** $_{i,t}$	
Independent Variables	Coefficient	t-statistics	Coefficient	t-statistics	Coefficient	t-statistics
Intercept	-0.03437	-1.63	-0.03011	-1.56	-0.03020	-1.56
AF $_{i,t}$	**0.81672** ***	**17.55**	**0.81205** ***	**17.64**	**0.81241** ***	**17.61**
(FSF $_{i,t}$ ***- AF*** $_{i,t}$***)***	**0.04732** ***	**2.85**	**0.07174** **	**2.39**	**0.07181** **	**2.39**
(FSF $_{i,t}$ ***- AF*** $_{i,t}$***) * POST*** $_{t}$			**-0.15544** ***	**-3.89**	**-0.15545** ***	**-3.89**
(FSF $_{i,t}$ ***- AF*** $_{i,t}$***) * POST*** $_{t}$ **** IFRS*** $_{i,t}$			**0.15688** ***	**3.70**		
(FSF $_{i,t}$ ***- AF*** $_{i,t}$***) * POST*** $_{t}$ **** IFRS_ENF*** $_{i,t}$					**0.17955** ***	**3.80**
(FSF $_{i,t}$ ***- AF*** $_{i,t}$***) * POST*** $_{t}$ **** IFRS_nonENF*** $_{i,t}$					**0.14881** ***	**3.20**
SIZE $_{i,t}$	0.00838 ***	3.64	0.00795 ***	3.58	0.00793 ***	3.56
LEV $_{i,t}$	-0.00982 ***	-3.64	-0.01026 ***	-3.78	-0.01031 ***	-3.80
LOSS $_{i,t}$	-0.02644 ***	-2.93	-0.02765 ***	-3.23	-0.02755 ***	-3.22
GOV $_{i,t}$	0.00231	1.00	0.00250	0.99	0.00254	0.99
GDP $_{i,t}$	0.00076 ***	3.17	0.00060 ***	2.90	0.00060 ***	2.85
FOLLOWING $_{i,t}$	-0.00011	-0.49	-0.00009	-0.39	-0.00008	-0.36
HORIZON $_{i,t}$	-0.00006	-0.60	-0.00006	1.54	-0.00006	1.56
Industry fixed effects	yes		yes		yes	
Firm-year observations	5,232		5,232		5,232	
Firms	1,160		1,160		1,160	
Adjusted R^2	0.5888		0.5930		0.5929	

Notes:
This table presents regression analyses explaining firms' actual ROE. See Table 1 Panel A for variable definitions. We use data before the truncation of extreme values for change variables (see Table 1 Panel C). We then truncate AFt, FSFt, ROEt, and (FSFt – AFt) for the regression analyses at the 1st and 99th percentiles. This ends in 5,232 firm-year observations from 1,160 unique firms. The regression is estimated with industry fixed effects using two-digit GICS classifications (not reported). We report t-statistics based on robust two-way clustered standard errors by firm and industry. *, **, and *** indicate significance at the 10, 5, and 1 % levels, respectively.

V. Conclusion

In this study, we provide insight into the effect of mandatory IFRS adoption on accounting quality in terms of the ability of a financial statement-based model to forecast a firm's profitability. We also provide insight into whether the improvement in analyst forecast accuracy around mandatory IFRS adoption is associated with an improvement in the accuracy of a financial statement-based model. We therefore provide insight not only into the effect of mandatory IFRS adoption on accounting quality but also into the mechanism through which mandatory IFRS adoption leads to improved analyst forecast accuracy (Fogarty and Rogers 2005; Abarbanell and Bushee 1997; Soliman 2008). Finally, we

investigate whether analysts place greater weight on financial statement-based forecasts after mandatory IFRS adoption.

We note that IFRS generally restricts a firm's recognition and measurement choices relative to local standards and argue that the limited discretion should lead to increased accuracy of financial statement-based forecasts of profitability. Our empirical tests are based on a sample of firms from 22 countries that adopted IFRS mandatorily and a control sample of firms from the US. We construct a model to forecast ROE based on financial statement analysis ratios. We create out-of-sample forecasts of ROE and calculate the forecast errors from the financial statement-based model and analyst forecasts. We test whether the financial statement-based forecast accuracy and the analyst concensus forecast accuracy improved around mandatory IFRS adoption.

We find a significant improvement in the accuracy of the financial statement-based forecast model from the pre- to the post-IFRS adoption period. We find significant improvement in the accuracy of analyst forecasts around IFRS adoption but only for firms in countries with concurrent improvements in enforcement. We also find that the improvement in the accuracy of financial statement-based forecasts is associated with the improvement in analyst forecast accuracy. Further, we show that analysts place the same weight on financial statement-based forecasts after mandatory IFRS adoption in countries with concurrent improvements in financial reporting enforcement and place less weight on financial statement-based forecasts after mandatory IFRS adoption in countries without concurrent enforcement changes. Finally, we document that financial statement-based forecasts provide incremental information for explaining year-ahead profitability over analyst forecasts after mandatory IFRS adoption, both for firms in countries that bundled and for firms in countries that did not bundle the adoption of IFRS with concurrent substantive changes in reporting enforcement.

Our findings provide important insights into the effect of mandatory IFRS adoption on the predictive ability of financial statements. They also provide insights into the relation between analyst forecasts and financial statement-based forecasts. These insights contribute to understanding the benefits of mandatory IFRS adoption and to understanding analysts' use of information in the forecasting process.

We note that our investigation focuses on analysts as the user of financial statements. We recognize, however, that analysts represent only one user group of financial statements. Despite this caveat, the study provides important insights for research and for practice.

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Teil 4

Improving Profitability Forecasts with Information on Earnings Quality

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Abstract

Prior literature documents the usefulness of the DuPont disaggregation for predicting firms' future profitability, operating income, and stock market returns. In addition, research also emphasizes the importance of earnings quality information. However, there is a lack of research examining how earnings quality affects forecasts of profitability. This paper explores whether different earnings quality factors moderate the accuracy of profitability forecasts. This study contributes to the existing literature along three dimensions. First, contrary to financial statement analysis studies, I find that changes in profit margin provide incremental information for predicting changes in future return on assets. After controlling for earnings quality factors, the incremental usefulness of this accounting signal increases significantly. Second, this paper contributes to the earnings quality literature by providing an approach as how to include this information into forecasts of profitability. In doing so, I incorporate the main drivers of earnings quality (i.e. fundamental performance and the accounting system) into profitability forecasts. Last, the paper adds to the literature on how capital market participants perceive accounting information. I document that both analysts and investors appear to efficiently incorporate earnings quality information in their investment decisions.

JEL classification: M41

Keywords: Financial Statement Analysis, Forecasting Profitability, DuPont Analysis, Earnings Quality, Conservative Accounting, Persistence, Growth, Return on Net Operating Assets

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1. Introduction

Research on financial statement analysis (FSA) documents the usefulness of accounting information predicting firms' future profitability (Ou and Penman [1989]; Ou [1990]; Abarbanell and Bushee [1997]; Fairfield and Yohn [2001]; Fairfield et al. [2003]). Research on earnings quality concludes that accounting information is dependent on firm's fundamental performance and its accounting system (Ball and Shivakumar [2005]; Dechow et al. [2010]). While prior work separately emphasizes the importance of FSA and earnings quality for informing external recipients of financial statements about firms' financial and operational performance, considerably less is known how earnings quality impacts the accuracy of FSA models.

In predicting future performance, textbooks and research suggest a variety of parsimonious variables that improve the predictability of future performance. Fairfield and Yohn [2001] and Soliman [2008] present evidence that ratio analysis, that systematically breaks down profitability (RNOA) into more specific ratios according to the DuPont disaggregation, provides incremental information on accounting signals studied in prior research. Despite the popular appeal of such forecast models, prior research overlooks that accounting information flowing into forecast models might be exposed to changes in firms' earnings quality. This shift could bias profitability ratios and consequently impair the accuracy of forecasts. My study probes the extent to which the accuracy of FSA forecast models can be explained by the quality of reported earnings. In other words, I unite distinct findings of two previously separate literature streams to investigate whether joint consideration improves predictions of firms' profitability.

I begin my empirical analysis by examining the relative importance of earnings quality in explaining one-year-ahead profitability changes. I document that the earnings quality information leads, in contrast to standard DuPont disaggregation, to higher in-sample explanatory power of one-year-ahead changes in RNOA and DuPont components. Contrary to previous findings, the change in profit margin seems to possess relative usefulness. My findings imply that disaggregated DuPont components are partially influenced by the quality of firms' reported earnings. In order to avoid inaccurate conclusions from time invariant in-sample parameter estimations for the accuracy of the forecast model (Poon and Granger [2003]), the paper also shows evidence in out-of-sample predictions as suggested by Lev et al. [2010]. I find that earnings quality enhanced forecast models are incrementally informative in predicting changes in year-ahead RNOA. I also find a statistically significant relation between earnings quality and forecast errors from DuPont prediction models.

The second part of this study addresses how earnings quality is reflected in market expectations of firm performance. Specifically, I investigate the behavior of two groups of market participants: analysts and investors. I find that analysts' forecasts are more closely related to earnings quality enhanced prediction models than to standard DuPont disaggregation models. Likewise, investors appear to efficiently incorporate earnings quality information into stock prices. Year-ahead returns from hedge portfolios that are formed by a simple trading heuristic, using the competing models of traditional and earnings quality enhanced profitability forecasts, do not yield excess returns.

I also conduct a number of additional analyses and robustness checks. I evaluate the relative improvement in forecast accuracy by using industry specific models (two-digit and four-digit SIC codes) and find no improvement in line with Fairfield et al. [2009]. I also compare the forecast accuracy of five year rolling regressions with annual cross-sectional regressions. I find no significant difference in performance.

My study makes several important contributions to the literature on forecasting with accounting ratios and earnings quality. First, I extend the literature on forecasting profitability in several ways. I demonstrate the incremental accuracy of earnings quality enhanced forecast models for future changes in profitability in-sample and out-of-sample. I show that changes in profit margin, in particular, are sensitive to changes in firms' earnings quality. Furthermore, I contribute to the FSA research more generally by showing that the change in profit margin has become incrementally useful for predicting year-ahead changes in RNOA over the last decade.

I also contribute to the earnings quality literature by investigating the association between changes in firms' earnings quality and forecast accuracy. I highlight how components, which partially capture the effect of the accounting system and firms' performance on earnings quality, can be operationalized into forecasts. I further confirm findings of Rajan et al. [2007] that growth and conservatism are substitutes for predicting future profitability. Last, my findings suggest that market participants efficiently use earnings quality information for making investment decisions. My results also have implications for the econometrical design of forecast models. Rolling regression models do not appear to be superior to forecasts that use annual cross-sectional regressions.

I organize the remainder of this study as follows: section 2 provides motivation, discusses prior literature and develops my hypotheses. Section 3 describes variable construction and the data sample. Section 4 presents empirical results and Section 5 contains robustness checks. Section 6 concludes.

2. Related literature and research question

2.1 Forecasting profitability in the FSA literature

Earlier research shows that FSA is useful in various contexts. Penman [2010] broadly partitions FSA research into three types: risk determination, valuation, and financial forecasting. Risk analysis encompasses the prediction of default probabilities (Campbell et al. [2008]; Beaver et al. [2012]) and takeovers (Raman [2013]), credit ratings (Blume et al. [1998]; Kim et al. [2013]) or the estimation of firms' risk premium (Nekrasov and Shroff [2009]). The objective of the valuation literature is to convert financial ratios into firm value (e.g. Nissim and Penman [2001]; Barth et al. [2005]). Profitability forecasting uses ratios to estimate future performance in terms of earnings (Fairfield et al. [1996]), cash-flows (Barth et al. [2015]) or stock returns (Mohanram [2005]; Piotroski and So [2012]).

The early ratio-based forecast models generally used a wide range of accounting data in an unstructured way (e.g. Ou and Penman [1989]; Lev and Thiagarajan [1993]; Setiono and Strong [1998]). The more recent accounting literature uses valuation frameworks to set up forecast models in stepwise manner. In this vein, DuPont analysis is used to disaggregate profitability in a structured way. It decomposes profitability, defined as return on net operating assets (RNOA), into profit margin (PM) and asset turnover (ATO):

$$RNOA_t = PM_t \times ATO_t = \frac{Operating\ Income_t}{Revenues_t} \times \frac{Revenues_t}{Operating\ Assets_t}$$

Beyond that, one can further disaggregate ATO and PM into its components so that profitability is dissected to provide more information about the composition of firms' overall profitability. This paper concentrates on the ability of PM and ATO to predict future profitability. PM captures the impact of sales on firms' profit or, in other words, the operating efficiency. ATO measures sales per the employed amount of operating assets, so how efficiently a firm uses its assets. By analyzing both components, one can reveal how efficiently revenues were generated by the assets and how the costs are controlled during this value creation process.

Research has documented the explanatory power of the DuPont disaggregation for both explaining current levels of profitability as well as for forecasting future profitability. By showing the association between equity value and profitability (RNOA) in the residual income valuation model, Nissim and Penman [2001] highlight how an understanding of the trend and persistence of RNOA and its components assists with valuation and forecasting. Fairfield and Yohn [2001] provide evidence that the DuPont disaggregation provides incremental

information for estimating one-year-ahead changes in RNOA. Soliman [2008] finds that analysts and investors do not fully impound the predictive information of PM and ATO in their decision making. Amir et al. [2011] differentiate between conditional (power of a DuPont ratio's persistence to explain the persistence of a variable higher up in the DuPont hierarchy) and unconditional persistence (measured as the first-order autocorrelation coefficient) of DuPont ratios and find that RNOA components exhibit varyingly conditional and unconditional persistence. Furthermore, they find that the market's reaction to PM is stronger than to ATO. Lately, Baik et al. [2013] use frontier analysis to demonstrate that operational efficiency (measured as ATO) is useful in predicting firm performance.

2.2 Earnings quality and the influence on profitability forecasts

Earnings are said to be of higher quality when they provide more information about the features of a firm's financial performance for decision making (Dechow et al. [2010]). Earnings quality thereby depends on the specific situation. This makes the term earnings quality conditional on the frame of reference. Even though a vast stream of accounting research on earnings quality demonstrates its consequences, for instance, on stock prices and returns (Callen et al. [2013]), cost of capital (Francis et al. [2008]), or information asymmetry (Bhattacharya et al. [2013]), little is known of how earnings quality impacts the forecast accuracy of ratio-based forecast models.

Earnings quality is jointly determined by both the accounting system and by the firm's fundamental performance (Barth et al. [2008]). Accordingly, if a firm experiences a change, either in its operating profitability or in its accounting system, it might also have an impact on earnings quality or, as a result, on the accuracy of an earnings forecast model. By omitting one of these partly joint earnings quality determinants, forecast models might lose information which lowers the explanatory power.

Previous forecast models in the FSA literature predominantly focus on firms' performance without considering the influence of the accounting system. However, the earnings quality literature presents growing evidence that firm performance and the accounting system both affect future profitability and market reactions. For example, Lipe [1986] and Sloan [1996] find differences in the persistence of earnings components, suggesting that forecasts should weigh the influence of each component differently. Amir et al. [2011] provide evidence that the market reacts differently to the conditional and unconditional persistence of DuPont ratios.

Another approach analyzing the impact of earnings quality on firms' future profitability is the examination of the total magnitude of accruals or the error term from regressing accruals on their economic drivers. Xie [2001] observes that non-discretionary accruals have more predictive ability than residuals from the Jones [1991] model for explaining one-year-ahead earnings. Dechow and Dichev [2002] conclude that accrual quality is positively related with earning quality proxies. These studies suggest that an extreme magnitude of accruals decreases earnings persistence and, ultimately, forecast accuracy. To this extent, Tucker and Zarowin [2006] find that firms which actively manage the smoothness of earnings (firms with a stronger negative correlation between discretionary accruals and earnings) provide earnings with more information about future earnings.

A further group of studies on earnings quality examines the consequences of the accounting system. Research investigates how the selection of accounting principles impacts the quality of accounting numbers disclosed in firms' financial statements. In this vein, great effort has been undertaken to understand the impact of conservative accounting on earnings and profitability ratios. Conservatism is broadly interpreted as the choice of accounting treatments that are likely to understate net assets and cumulative income (e.g. Revsine et al. [2005]). More recent research distinguishes between unconditional and conditional conservatism. Unconditional conservatism reflects the application of conservative accounting policies (e.g. expenditure of R&D and advertising) whereas conditional conservatism is event-driven (e.g. different timeliness of recognizing towards unfavorable information faster than towards favorable information; Beaver and Ryan [2005]). Normative and empirical research examine how the joint influence of conservative accounting and growth in investments affect earnings quality. Under conservative accounting, firms build reserves and understate their reported earnings when investments in operating assets increase. In contrast, if investments decrease, built reserves could get released. Either way, changes in growth under conservative accounting affect earnings quality due to earnings becoming temporarily bloated or inflated. Ignoring these changes could consequently distort forecasts which naively fixate on earnings as reported in the financial statements. Beaver and Ryan [2000] find that the association of conservatism in combination with growth and future book return on equity is less negative for firms with higher investments. Penman and Zhang [2002] develop a diagnostic measure that captures the joint effect of conservative accounting and growth on earnings quality. The diagnostic measure predicts differences of firms' future profitability and stock returns, indicating the usefulness of information on earnings quality in forecast models. Rajan et al. [2007] analytically and empirically investigate the joint effect of conservatism and growth on return on investments (ROI). Explaining the joint impact of both variables on future ROI, they find that these two variables are substitutes. They argue that,

under conservative accounting, growth not only tends to lower ROI, but also initiates a downward effect where more conservatism further magnifies this joint effect. This contradicts previous beliefs regarding how conservatism and growth interact.

These earnings quality studies have documented an association between firm performance and the application of accounting principles on the one side, and their explanatory power for future earnings on the other side. However, there still exist certain caveats for transferring this knowledge into profitability forecast models. First, previous research on earnings quality is more fixated on revealing accounting anomalies that were not perceived by market participants rather than on developing an understanding of how earnings quality affects future profitability. As a result, the earnings quality literature and the FSA literature were often treated as detached research areas. Fundamental analysis investigates how an analysis of firm performance provides information about future profitability. Earnings quality studies investigate how the accounting choices and the quality of accounting performance indicators, as disclosed in firms' financial statements, provide information about future profitability. This paper attempts to bridge the gap between these parallel research areas by analyzing how the creation of firm performance interacts with the measurement quality of accounting profitability.

Second, the previous literature generally does not discern between accounting information and external sources of information when developing forecast models.[1] In comparison to the accounting anomaly literature that uses both accounting information and market information in forecasts, I constrain the information set purely to balance sheet and income statement items. By using a closed accounting model without external influences such as market expectations, I mainly reduce the influencing factors on forecasts' accuracy to firm performance and earnings quality.

Third, there is mixed evidence on whether the joint impact of conservatism and growth provides explanatory power for future profitability (Penman and Zhang [2002]), or whether they are substitutes (Rajan et al. [2007]). Although the valuation literature emphasizes the influence of monopoly returns as they occur from firms' ability to sustain abnormal earnings relative to its market peers, there is no evidence as to whether past persistence enhances the predictability of future returns. I provide evidence that the persistence of different profitability components helps to explain future RNOA.

[1] Mohanram [2005], among other studies, is an example how FSA literature does not clearly separate accounting and market information. Even though some papers enhance forecast models with proxies for earnings quality, influences from other proxies prevent drawing conclusion on the distinct influence of earnings quality on profitability forecasts.

Drawing on previous literature, I try to capture the impact of earnings quality with two proxies. The first proxy captures earnings quality that originates from the fundamental performance of a firm. This proxy enhances the fundamental ratios from the DuPont disaggregation to explain fundamental firm performance in more detail. I assume that firms with more stable profitability also disclose earnings of higher quality since the variance of reported earnings decreases which facilitates the prediction of future earnings. Under this assumption, the paper uses the persistence of fundamental performance as a proxy for earnings quality. But the persistence of profitability also depends on the accounting measurement system. In order to overcome this shortcoming, the paper adds a second proxy for the influence of the accounting system on earnings quality. I discuss the proxy for the accounting system in section 3.1 in more detail. This way, I cover two main components of earnings quality, the influence of the firm performance and of the accounting system.

I address the influence of earnings quality on profitability forecasts (*ΔFuture Profitability)* by expanding a traditional ratio-based forecast model (*FSA-Model*) with earnings quality (*EQ*) of firms' performance and the accounting system:

$$\Delta \text{ Future Profitability} = f(\text{ FSA-Model} \mid EQ \text{ })$$

The prediction of future changes in profitability thus becomes a function of a FSA forecast model using traditional DuPont disaggregation and proxies for earnings quality which capture the effects of changes in firms' performance and effects of changes in the accounting system.[2]

Taken together, prior literature shows that forecasts based on accounting numbers, and DuPont analysis in particular, are useful for predicting future profitability and market reactions. Another strand of literature emphasizes the impact of earnings quality on historical and future profitability. By comparing the in-sample explanatory power and out-of-sample forecast errors from traditional forecasts against earnings quality enhanced forecasts, I provide empirical evidence on the incremental usefulness of each factor.

[2] Drawing on findings from Fairfield and Yohn [2001] who find that DuPont components are only useful for predicting the future change in profitability but not the level, I focus my research on year-ahead changes in profitability.

2.3 Hypothesis development

FSA literature has shown the usefulness of accounting information for the prediction of future profitability (Fairfield and Yohn [2001]; Soliman [2008]). The earnings quality literature has shown the impact of performance and accounting system related influences on future profitability (Dechow et al. [2010]). But impacts from both factors were analyzed separately. Furthermore, the previous literature did not separately distinguish between pure accounting information and additional external information. So ex ante, the impact of earnings quality on accounting profitability forecast models is not clear. This leads to the first hypothesis in the null form:

H1: Information on earnings quality in accounting forecast models does not provide additional explanatory power about firms' future profitability.

In this context, the next question that naturally rises is whether profitability forecasts complemented with information on earnings quality could improve traditional forecast models. Improvements would mean that earnings quality does not only display an association between future profitability in an in-sample framework but also in out-of-sample tests. Therefore, the second hypothesis, in the null form, is:

H2: The usefulness of accounting information for predicting future profitability does not improve after the adjustment for earnings quality.

The last part of the paper considers the question of whether market participants efficiently use earnings quality information. As a first group of market participants, I analyze whether financial analysts efficiently incorporate earnings quality information into their decision-making process, or alternatively, in the null form:

H3: Financial analysts do not incorporate information about earnings quality in their decision making process.

The second question addressed here is whether information on earnings quality is associated with market returns. With the employment of a long-window return test (12-month annual return test), I survey the value relevance ('Interpretation 4' of value relevance as suggested by Francis and Shipper [1999]) that investors devote to earnings quality in their forecasts. Accordingly, the third hypothesis is in its null form:

H4: Profitability forecasts, adjusted for earnings quality, do not deliver additional information about future market returns.

3. Research design and data

3.1 Measuring earnings quality

Prior research emphasizes a wide range of different market-based and accounting-based attributes to characterize earnings quality (see. Francis et al. [2004] for a review).[3] Since my analyses are confined to financial statement information, I exclusively focus on accounting-based proxies. Dechow et al. [2010] highlight that earnings quality is jointly determined by the relevance of underlying financial performance and by the ability of the accounting system to measure performance. In practice, however, it is hard to disentangle these two determinants into mutually exclusive proxies. The following section explains the specific selection of two earnings quality proxies out of this wide range of suggested proxies in the accounting literature and why I assign them to explain the influence either from fundamental performance or from the accounting system.

Figure 1 depicts the disaggregation of RNOA into its first and second-order components. Standard DuPont analysis captures on the first-order decomposition the influence and persistence of ATO and PM as they contribute to firms' profitability. In doing so, PM measures the change in firms' ability to control costs while generating revenues. ATO measures the change in asset utilization and efficiency in generating revenues. Regular slope coefficients of ATO and PM in a regression model on future RNOA cannot distinguish whether fundamental performance or the accounting system drives firms' performance. This lack of information could distort forecasts. For instance, a firm could compensate for diminishing returns from mean reversion in its markets (e.g. new competitors, lower demand) by releasing hidden reserves, built by applying conservative accounting principles, into earnings. Up to a certain degree, the release of those reserves through changes in the accounting system could reduce the diminishing returns. But once it has reached a certain threshold where all reserves are expended, PM is likely to decrease by the adverse market conditions.

To integrate earnings quality influences in DuPont analysis, I investigate the impact of earnings quality proxies as they emerge from fundamental performance, not only by the slope coefficients of ATO and PM but also by disaggregated second-order components. A decline (increase) in PM could either occur through increasing (decreasing) costs as indicated by net income (NOI) in the numerator or through diminishing (ascending) revenues (e.g. changes in sales rates and sales prices) in the denominator, or both. With regard to

[3] For instance, Francis et al. [2004] consider seven properties that are desirable features of earnings: accrual quality, persistence, predictability, smoothness, value relevance, timeliness, and conservatism.

fundamental performance, the persistence[4] of NOI may reflect how operating efficiency is influenced by shifts in the cost structure. A stable PM ratio might therefore indicate persistent earnings or, alternatively, an adaptable accounting system (adoption of more liberal or more conservative accounting principles) that compensates for the lack of fundamental performance. To control for the influence of accounting principles, one needs a proxy for conservatism[5] that captures the quality of reported earnings as reported by PM. Accordingly, changes in ATO may result due to changes in sales or to the productive use of assets. The choice of using different accounting principles does not only affect firms' income statement by recognizing expenditures like R&D or advertisements, but also firms' balance sheet which influences ATO (e.g. LIFO accounting is more conservative than FIFO accounting since it carries lower LIFO amounts). Therefore, the persistence of sales indicates the share of recurring revenues that contribute to firms' fundamental profitability, whereas a measure for conservatism on the balance sheet indicates an estimation to what extent the accounting system influences firm's profitability ratios.

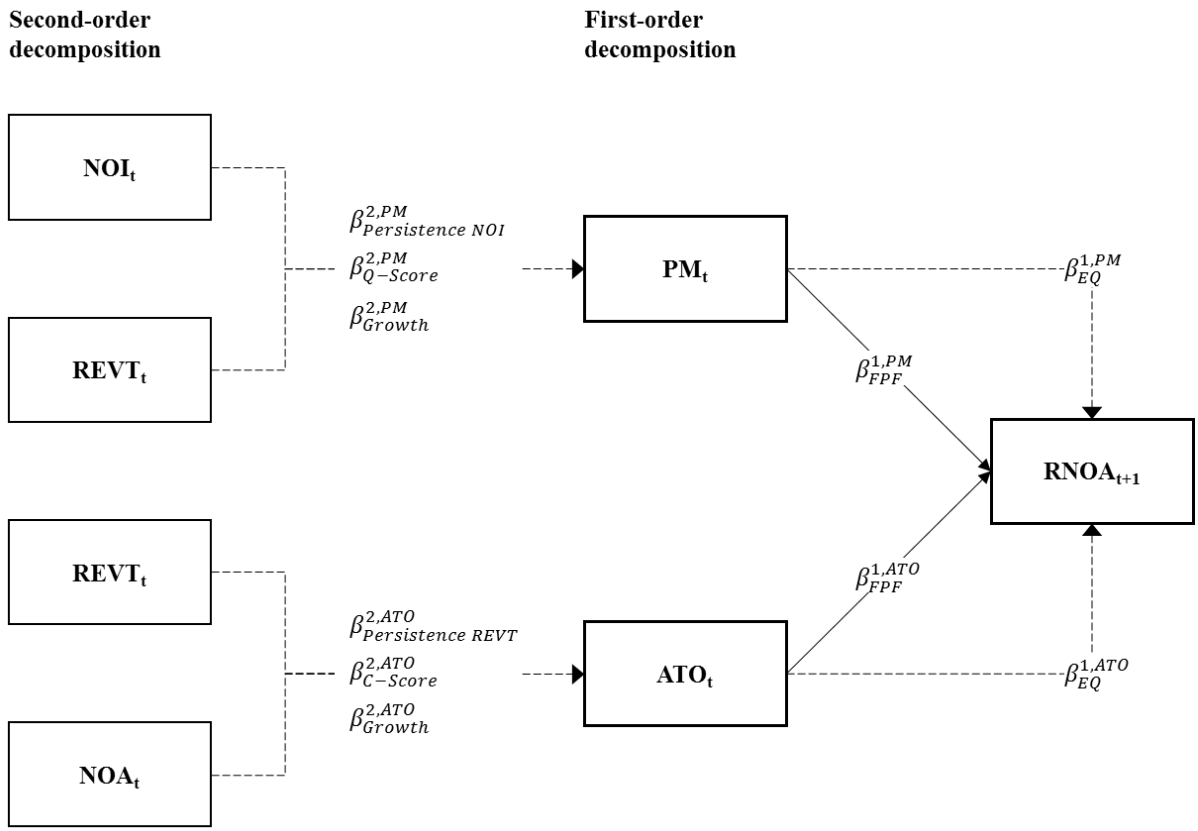
Last, I control how growth in both, ATO and PM, affects future profitability. Thereby, growth is not seen as a proxy for earnings quality but rather as a control variable that is found to interact with profitability components and earnings quality proxies (e.g. conservative accounting). I therefore interact growth with second-order DuPont components and add growth as separated control variable to the forecast model as suggested in the FSA literature (e.g. Fairfield and Yohn [2001]).

To identify the effect of these earnings quality proxies on future profitability, I interact each proxy as they appear from second-order decomposition with ATO and PM, respectively. This way, I modulate a conditional association between the influence of earnings quality on first-order components and future profitability. Figure 1 illustrates how interactions between first and second-order effects detangle the influence of fundamental performance and the impact of earnings quality for predicting one-year-ahead RNOA.

[4] Dechow et al. [2010] find earnings persistence the most used proxy for earnings quality in equity valuation frameworks to describe the sustainability of firm performance. Since forecasting exhibits distinct similarities to valuation frameworks, I tie on this literature stream by using earnings persistence rather than the smoothness of earnings or the like.

[5] Earnings quality gets influenced by an array of different determinants from the accounting system. However, most of those determinants are opaque and couldn't be conceived by studying firms' financial statements. Penman and Zhang [2002] suggest for this purpose a parsimonious ratio estimating the degree to which firms apply conservative accounting principles. I adopt this methodology because all information are disclosed in financial statements without the need of any further external sources.

Figure 1: Unconditional and conditional relation between first and second order components of DuPont analysis with one-year-ahead RNOA



Notes:
Figure 1 shows the first and second-order DuPont decomposition. See Appendix 1 for variable definitions. The direct link between PM/ATO ($\beta^{1,ATO}_{FPF}/\beta^{1,PM}_{FPF}$) and RNOA modulates the aggregated influence of firms' unconditional fundamental performance as it arises from the first-order DuPont decomposition. The conditional association between PM/ATO and RNOA is constructed via an indirect link that detangles earnings quality influences as they arise from the persistence of NOI and REVT and conservative accounting. The influence of growth is also added as control. By interacting ATO/PM with these earnings quality proxies, one indirectly creates a conditional link ($\beta^{1,ATO}_{EQ}/\beta^{1,PM}_{EQ}$) between the second-order and the first-order decomposition for explaining one-year ahead RNOA.

This paper follows Barton et al. [2010] by defining the persistence of the DuPont component *X* of firm *i* at time *t* as the slope coefficient $\beta_{i,1}$ in the first-order autoregressive model:

$$X_{i,t} = \alpha_{i,0} + \beta_{i,1} X_{i,t-1} + \varepsilon_{i,t}$$

I measure the persistence of two second-order DuPont components: First, the persistence of net operating income (NOI) indicates the stability of firms' profit margin by generating a steady stream of net income. Second, the persistence of revenues (REVT) explains the sustainability of asset turnover attributable to recurring revenues. For each observation, I run firm individual regressions over the past four years. Higher values of $\beta_{i,1}$ indicate more

persistent performance. More sustainable performance is likely to be a more useful input into forecast models. Consequently, the quality of accounting information gets more valuable.

The proxy for the quality of the accounting system is the degree to which firms practice conservative accounting. Francis et al. [2004] characterize conservatism as a market-based proxy since it is intended to measure the differential ability of accounting earnings to reflect economic losses (negative stock returns) versus economic gains (positive stock returns). However, since further analyses are constrained by a closed accounting framework, I follow the Penman and Zhang [2002] measure that aggregates indicators of conservatism from both the balance sheet and the income statement into a scoring system. The so called C-Score thus represents an accounting-based proxy rather than a market-based proxy for conservatism. The C-Score measures the effect of conservative accounting on the balance sheet by summing up capitalized R&D ($XRD_{i,t}$), capitalized advertising expense ($XAD_{i,t}$), and LIFO reserves ($LIFR_{i,t}$).[6] These unrecorded reserves originated by operating items in the balance sheet are then scaled by $NOA_{i,t}$:

$$C_{i,t} = \frac{LIFR_{i,t} + XAD_{i,t} + XRD_{i,t}}{NOA_{i,t}}$$

Whereas the C-Score captures the impact of conservative accounting for the effectiveness of asset utilization (ATO), the Q-Score measures the impact of conservatism on OI in the income statement. Again, I follow Penman and Zhang [2002] by defining the Q-Score as the weighted sum of one-year change in firm's C-Score ($Q_{i,t}^{firm}$) and firm's C-Score in relation to the total market[7] ($Q_{i,t}^{market}$):

$$Q_{i,t} = \left(0.5 \times Q_{i,t}^{firm}\right) + \left(0.5 \times Q_{i,t}^{market}\right)$$

where

$$Q_{i,t}^{firm} = C_{i,t} - C_{i,t-1}$$

$$Q_{i,t}^{market} = C_{i,t} - market\ median(C_{i,t})$$

The last earnings quality proxy is growth. Growing investments in operating assets not only influence firms' fundamental performance (Fairfield et al. [2003]) but also the impact of

[6] Following Balachandran and Mohanram [2011], I capitalize and amortize R&D over five years and advertising expenses over two years, using sum-of-years-digits amortization. If observations on R&D and advertising are missing, I set them to zero.

[7] Penman and Zhang [2002] use the industry mean. For the sake of statistical power, I use again the market average. In control tests, I also use the industry average. Results do not change.

conservative accounting (Rajan et al. [2007]). Therefore, the influence of growth on earnings quality is neither exclusively assigned to fundamental performance nor to the accounting system. I define growth as the yearly change in NOA since operating activities and operating assets mainly drive firm value (Ohlson [1995]).

3.2 Forecasting approaches

The main research design consists of three steps. The first step examines the in-sample relation of earnings quality proxies on DuPont analysis forecasts. Next, I evaluate the out-of-sample performance with the same evaluation metric as in step one. Finally, I investigate how market participants use earnings quality information for predicting future firm performance and stock market performance.

Following previous literature (e.g. Fama and French [2000], Fairfield and Yohn [2001]), in-sample estimations are conducted with yearly cross-sectional regressions. To demonstrate the influence of earnings quality on the explanatory power of future profitability, I contrast the earnings quality adjusted forecast model against an established forecast model that embraces findings from prior research for explaining $\Delta RNOA_{t+1}$:

BM-Model:
$$\Delta RNOA_{t+1,(i)} = \alpha_i + \beta_1 RNOA_{t,(i)} + \beta_2 \Delta ATO_{t,(i)} + \beta_3 \Delta PM_{t,(i)} + \\ + \beta_4 \Delta INT_{t,(i)} + \beta_5 \Delta NOA_{t,(i)} + \varepsilon_{t+1,(i)}$$

EQ-Model:
$$\Delta RNOA_{t+1,(i)} = \alpha_i + \beta_1 RNOA_{t,(i)} + \beta_2 \Delta ATO_{t,(i)} + \beta_3 \Delta PM_{t,(i)} + \beta_4 \Delta INT_{t,(i)} + \\ + \beta_5 \Delta ATO_{t,(i)} * \gamma_{t,(i)} + \beta_6 \Delta ATO_{t,(i)} * \kappa_{t,(i)} + \beta_7 \Delta ATO_{t,(i)} * \pi_{t,(i)} + \\ + \beta_8 \Delta PM_{t,(i)} * \gamma_{t,(i)} + \beta_9 \Delta PM_{t,(i)} * \kappa_{t,(i)} + \beta_{10} \Delta PM_{t,(i)} * \pi_{t,(i)} + \\ + \beta_{11} \Delta NOA_{t,(i)} + \varepsilon_{t+1,(i)}$$

where,

$\gamma_{t,(i)}$: Growth in net operating assets (ΔNOA)

$\kappa_{t,(i)}$: Conservative accounting. The EQ-Model applies the yearly change of the C-Score for *ΔATO*, and the Q-Score for *ΔPM* (the Q-Score already contains the yearly change of the C-Score)

$\pi_{t,(i)}$: Persistence of profitability components. The EQ-Model utilizes the persistence of sales for *ΔATO*, and persistence of earnings (NOI) for *ΔPM*

$t, (i)$: year *t,* firm *i*

The benchmark model (BM) disaggregates the change in current RNOA into changes in ATO and PM. Following findings from Fairfield and Yohn [2001], the model additionally includes the actual level of RNOA and a variable labeled ΔINT that captures the interaction between ΔPM and ΔATO. The variable ΔINT originates from the mathematical transformation of ΔRNOA along the DuPont disaggregation as shown in Fairfield and Yohn [2001] and is added to our forecast model for the sake of completeness. The BM-Model accordingly serves as a benchmark model for previous findings in the literature on forecasting future profitability.

The earnings quality enhanced model (EQ-Model) additionally incorporates earnings quality information. I interact both DuPont components ΔATO and ΔPM with proxies that capture the effects from fundamental performance and the accounting system on earnings quality. Previous research also argues that capital expenditures have a negative association with future earnings (e.g. Ou [1990], Abarbanell and Bushee [1997]). To validate that my findings are not solely a result of growth, I add the change in net operating assets to both models.

Lev et al. [2010] motivate research not merely to investigate the explanatory power of forecasts in-sample but rather as a challenge that real investors have to face. This is to test the usefulness of a model not only backward but also forward in an out-of-sample prediction. I use the same data and models for the out-of-sample prediction as the in-sample estimation. To provide higher inter-temporal stability for in-sample coefficients, I use rolling 5-year regressions. The out-of-sample forecast of ΔRNOA in 2000, for instance, refers to in-sample coefficients that are estimated from 1994 to 1998 to explain ΔRNOA in 1999. These in-sample coefficients are applied to data from 1999 to forecast ΔRNOA in 2000 out-of-sample.

3.3 Sample

The sample of this study starts with 72,581 U.S. firm-year observations (10,479 unique firms) in the COMPUSTAT dataset in the period from 1990 through 2012, for which sufficient information is available to calculate all independent and dependent variables. Financial firms and institutes with SIC codes from 6000 to 6999 are excluded. Appendix 1 summarizes the variable definitions used for the in-sample coefficients and analyses. For distinguishing between operating and financial activities, I refer to the approach suggested by Callen and Segal [2005]. To further mitigate concerns that extreme observations drive the results for the

in-sample estimation and out-of-sample prediction, I comprehensively eliminate firms based on several criteria. First, I exclude firms with negative values for several DuPont coefficients and components that are needed to calculate earnings quality proxies in year t (11,473 observations). To reduce the effect of mergers and acquisitions, I delete firms with growth in NOA that is greater than 100 percent in t (1,244 observations). Outliers with changes in DuPont components that exceed 50 percent are also excluded (13,640). Firms with missing or extreme values for earnings quality proxies (conservatism and persistence) are removed (14,306). Finally, all in-sample coefficients are winsorized at the 1 percent level from both sides. These criteria yield in a final sample of 17,808 firm-years and 3,776 unique firms for in-sample estimations. All sample adjustments are consistent with previous studies on DuPont analysis (Fairfield and Yohn [2001]; Soliman [2008]) in order to facilitate comparison among studies. For out-of-sample forecasts, I do not apply any screenings for the predicted variable ($\Delta RNOA_{t+1}$) to avoid a look-ahead-bias. Finally, all observations before 1996 that are used for the in-sample estimation are excluded. This results in 12,478 firm-years and 3,015 unique firms with out-of-sample forecasts from 1996 through 2012. Table 1 resumes the data selection process.

Table 1: Sample Selection

In-sample estimation and out-of-sample forecast	**Firm-years**	**Unique firms**
US firm-year observations between 1990 and 2012 with sufficient data to calculate independent and dependent variables	72,581	10,479
less firm-year observations characterized by:		
Financial industry classification and possessing segments according to the Global Industry Classification Standard	11,473	1,968
Negative observations for NOA_t, ATO_t, PM_t, XAD_t, XRD_t, $LIFR_t$	14,110	1,269
Absolute percentage change in NOA_t, NOA_{t+1} > 100%	1,244	82
Absolute percentage change in $RNOA_t$, $RNOA_{t+1}$, ATO_t, ATO_{t+1}, PM_t, PM_{t+1} > 50%	13,640	1,530
Absolute value of C-Score$_t$ = 0 or > 5 and of persistence > 1	14,306	1,854
All variables for the insample-estimation were winsorized at the 1% level from both sides		
Observations used for the forecast model	**17,808**	**3,776**
Analyses		
excluding firm-year observations from analyses with:		
Observations before 1996 used for in-sample estimation	5,330	761
Observations used for anlyses	**12,478**	**3,015**

3.4 Descriptive statistics and correlations

Table 2 presents the descriptive statistics and correlations for the variables used in this study. Panel A reports the descriptive statistics for all firm-years in the in-sample estimation. Most of the values are consistent with prior literature. The mean and median of $\Delta RNOA_{t+1}$ is more negative than in older studies (e.g. Fairfield and Yohn [2001]). In addition to the mean reverting tendency of $\Delta RNOA_{t+1}$, further analyses (not reported) reveal that yearly changes in RNOA got more negatively pronounced values during the financial crises between 2007 and 2009 (-1.79% on average). However, the change in profit margin (ΔPM_t) exhibits for both the mean (1.47%) and median (0.67%) positive values. Accounting conservatism, measured as C-Score (0.086 on average) and Q-Score (0.059), are likewise comparable to recent research (Balachandran and Mohanram [2011]). Revenues exhibit the most stable persistence (0.60 on average), whereas earnings (0.16) possess far less sustainability.

Panel B presents Pearson and Spearman rank correlations among the variables. Most of the correlation coefficients are statistically different from zero. Most earnings quality proxies show a statistically significant correlation with actual first-order DuPont components (ΔATO_t and ΔPM_t) and with one-year-ahead changes in RNOA. Growth (ΔNOA_t) and $\Delta RNOA_{t+1}$ correlate negatively. Persistence in firms' net income and revenues exhibit a significantly negative correlation between $\Delta RNOA_{t+1}$ what indicates mean-reversion for firms with highly sustainable income and sales in the past.[8]

[8] To avoid the influence of highly correlated coefficients in subsequent analyses, I additionally test if values for persistence of NOI and REVT (second-order persistence) and values for persistence of ATO and PM display multicollinearity. Tests reject this concern.

Table 2: Descriptive statistics and correlations for variables used to estimate in-sample regression coefficients

Panel A: Descriptive statistics

Variables	Mean	Median	STD	Q1	Q3	Min	Max
$\Delta RNOA_{t+1}$	-0.01808	-0.00502	0.09497	-0.05546	0.03225	-0.35746	0.21954
$\Delta RNOA_t$	0.01408	0.00635	0.09347	-0.03195	0.04885	-0.23758	0.34996
RNOA	0.18289	0.15449	0.13010	0.09228	0.23943	0.00722	0.68794
ATO_t	2.02500	1.84383	1.03278	1.31602	2.49325	0.39687	5.89607
PM_t	0.10260	0.08664	0.07212	0.05055	0.13550	0.00405	0.36370
ΔATO_t	-0.00333	-0.00044	0.02201	-0.01212	0.00757	-0.08461	0.05757
ΔPM_t	0.01469	0.00668	0.08673	-0.02524	0.04345	-0.22041	0.33687
ΔINT_t	0.00009	0.00001	0.00225	-0.00019	0.00034	-0.01100	0.01018
ΔNOA_t	0.08899	0.05216	0.18805	-0.02606	0.15960	-0.25803	0.88590
C-$Score_t$	0.08559	0.05277	0.09534	0.02010	0.11666	0.00000	0.50557
Q-$Score_t$	0.05904	0.02624	0.09512	-0.00614	0.08958	-0.02872	0.47890
Persistence $Revenues_t$	0.60366	0.67580	0.58923	0.18603	1.03253	-0.87899	1.82965
Persistence $Earnings_t$	0.16267	0.09375	0.58748	-0.24365	0.56418	-1.27166	1.60365

Panel B: Spearman / Pearson (above) correlations

	$\Delta RNOA_{t+1}$	$\Delta RNOA_t$	$RNOA_t$	ΔATO_t	ΔPM_t	ΔINT_t	ΔNOA_t	C-$Score_t$	Q-$Score_t$	Persistence $Revenues_t$	Persistence $Earnings_t$
$\Delta RNOA_{t+1}$	**1.000**	-0.039	-0.118	0.098	-0.068	-0.022	-0.115	-0.005	*-0.003*	-0.036	-0.043
$\Delta RNOA_t$	*-0.004*	**1.000**	0.076	0.263	0.970	-0.323	-0.105	0.084	0.085	-0.087	-0.101
$RNOA_t$	-0.143	0.113	**1.000**	*0.010*	0.087	0.042	0.169	0.205	0.205	0.219	0.326
ΔATO_t	0.114	0.351	0.059	**1.000**	0.065	-0.062	-0.271	0.023	0.023	*0.004*	-0.045
ΔPM_t	-0.043	0.943	0.137	0.108	**1.000**	-0.336	-0.031	0.075	0.076	-0.078	-0.079
ΔINT_t	*-0.010*	-0.131	0.052	*0.009*	-0.176	**1.000**	0.060	*0.004*	*0.004*	*0.004*	-0.017
ΔNOA_t	-0.158	-0.131	0.244	-0.251	-0.042	0.030	**1.000**	-0.094	-0.096	0.246	0.209
C-$Score_t$	0.013	0.073	0.174	0.024	0.065	*0.010*	-0.067	**1.000**	0.999	-0.044	-0.037
Q-$Score_t$	0.016	0.075	0.172	0.026	0.067	*0.012*	-0.073	0.996	**1.000**	-0.047	-0.038
Persistence $Revenues_t$	-0.053	-0.067	0.268	0.020	-0.055	-0.027	0.304	-0.033	-0.040	**1.000**	0.324
Persistence $Earnings_t$	-0.068	-0.097	0.326	-0.045	-0.062	-0.049	0.215	-0.030	-0.033	0.337	**1.000**

Notes:
See Appendix 1 for variable definitions. Panel A provides summary statistics for the 17,808 firm-years (3,776 unique firms) for the sample period between 1990 and 2012. Panel B shows Spearman (Pearson) correlations below (above) the diagonal. All correlations in italic are not significant at and below the 10% level.

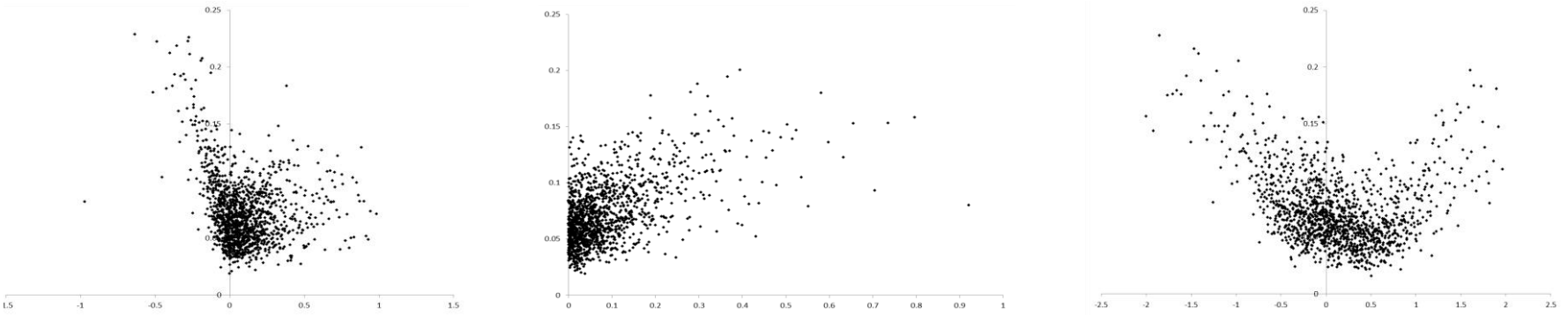
4. Empirical results

4.1 Relative usefulness of earnings quality information in accounting forecast models for explaining and predicting future profitability

Does the quality of reported earnings affect the predictability of future profitability? Figure 2 presents results from the BM-Model that estimates one-year-ahead changes in profitability by disaggregating profitability into changes in asset turnover and changes in profit margin as suggested in FSA textbooks (e.g. Lundholm and Sloan [2012]; Penman [2012]). The methodology is conducted as in Fairfield and Yohn [2001]. Detailed statistics concerning the in-sample estimation and the out-of-sample forecast are reported in the following sections. To motivate my research question that earnings quality factors could impact profitability predictions, I sort absolute forecast errors by proxies for earnings quality: accounting conservatism, growth, and persistence. As can be observed from all three plots, the accuracy of predicting future changes in profitability ($\Delta RNOA_{t+1}$) almost linearly decreases with absolute increasing values of each individual proxy for earnings quality. Increased growth in assets and increased divestitures in firms' assets raise the likelihood of higher forecast errors resulting from the ratio-based forecast model. The same applies to conservative accounting. Financial statements that are subject to more conservative accounting appear to bias not only the forecast accuracy of analysts (Mensah et al. [2004]) but also ratio-based prediction models. Last, Figure 2 demonstrates the dispersion of forecast errors as a function of earnings persistence. Between values of the persistence measure from -0.5 - 0 as well as 0 - 0.5, one observes a threshold where forecast errors gradually increase with lower/higher earnings persistence. However, as the coefficient amplifies, the error rate noticeably leaps. This observation contradicts the intuition of earnings persistence because a more persistent earning stream should indicate a more useful summary measure for future profitability (Dechow et al. [2010]).

The results from prior FSA literature, earnings quality literature, and Figure 2 together suggest that earnings quality may influence profitability forecasts.

Figure 2: Association between accuracy of DuPont analysis based forecasts and different degrees of growth, conservatism, and persistence



Growth **Conservatism** **Persistence**

Notes:
Figure 2 shows the relation between the level of absolute forecast errors (y-axis) from out-of-sample forecasts using DuPont analysis (prediction of $\Delta RNOA_{t+1}$) under different levels of growth (ΔNOA_t), conservatism (C-$Score_t$) and persistence of profitability (persistence $RNOA_t$). See Appendix 1 and section 3.1 for variable definitions. The forecast approach is described in section 3.2 (BM-Model). Table 3 and 4 report in-sample and out-of-sample statistics of the forecast model and forecast errors in detail. Each dot represents the mean of 10 out-of-sample forecast errors (total=12,478 firm-years) from 1996 to 2012.

4.1.1 Results from in-sample regressions

The first empirical analysis considers the research question whether information about earnings quality of firms' performance and accounting system increases the explanatory power of accounting forecasts for predicting one-year-ahead changes in profitability. The prediction of future changes in profitability ($\Delta RNOA_{t+1}$) from in-sample regressions is shown in Table 3. Pooled regressions are exposed to cross-sectional correlation in the residuals (Bernard [1987]). I therefore estimate all coefficients from the rolling regression for each year and, accordingly, report mean coefficient estimates and the associated t-statistics as suggested by Fama and MacBeth [1973]. Following Bernard [1995], I also adjust coefficient estimates for cross-sectional correlation according to the Newey and West [1987] approach. The goodness of fit of each model is measured as the mean value of all average annual adjusted R^2s. Barth et al. [2001] attribute R^2 usefulness for comparing and evaluating prediction models.

Table 3: In-sample coefficients estimates (1990 – 2012)

BM-Model: $\Delta RNOA_{t+1,(i)} = \alpha_0 + \beta_1 RNOA_{t,(i)} + \beta_2 \Delta ATO_{t,(i)} + \beta_3 \Delta PM_{t,(i)} + \beta_4 \Delta INT_{t,(i)} + \Delta NOA_{t,(i)} + \varepsilon_{t+1,(i)}$

EQ-Model: $\Delta RNOA_{t+1,(i)} = \alpha_0 + \beta_1 RNOA_{t,(i)} + \beta_2 \Delta ATO_{t,(i)} + \beta_3 \Delta PM_{t,(i)} + \beta_4 \Delta INT_{t,(i)} + \beta_5 \Delta ATO_{t,(i)} * \gamma_{t,(i)} + \beta_6 \Delta ATO_{t,(i)} * \kappa_{t,(i)} + \beta_7 \Delta ATO_{t,(i)} * \pi_{t,(i)} + \beta_8 \Delta PM_{t,(i)} * \gamma_{t,(i)} + \beta_9 \Delta PM_{t,(i)} * \kappa_{t,(i)} + \beta_{10} \Delta PM_{t,(i)} * \pi_{t,(i)} + \beta_{11} \Delta NOA_{t,(i)} + \varepsilon_{t+1,(i)}$

Model	**BM-Model**			**EQ-Model**		
Estimation Method	*OLS by year*			*OLS by year*		
Dependent Variable	**$\Delta RNOA_{t+1}$**			**$\Delta RNOA_{t+1}$**		
Variables	**Coefficients**		**t-statistics**	**Coefficients**		**t-statistics**
Intercept	0.00202		0.60	0.00168		0.52
$RNOA_t$	-0.06972	***	-9.95	-0.06944	***	-11.43
$\Delta RNOA_t$						
ΔATO_t	0.37717	***	8.07	0.33894	***	13.13
ΔPM_t	-0.09254	***	-3.45	-0.12119	***	-6.65
ΔINT_t	-1.39392	*	-1.91	-1.22844	*	-1.69
$\Delta ATO_t * \gamma_t$				-0.00915		-0.70
$\Delta ATO_t * \kappa_t$				0.01823		0.45
$\Delta ATO_t * \pi_t$				0.00899		1.51
$\Delta PM_t * \gamma_t$				0.10972		1.11
$\Delta PM_t * \kappa_t$				0.48354	**	2.41
$\Delta PM_t * \pi_t$				0.02185		0.64
Growth in NOA_t	-0.03650	***	-4.90	-0.03709	***	-3.72
Firm Years		17,808			17,808	
Unique Firms		3,776			3,776	
Adjusted R^2		3.611%			3.825%	

Differences in adjusted-R^2
Vuong test (Z-statistic)

	EQ-Model
BM-Model	4.27***

Notes:
This table presents the in-sample regressions of one-year ahead RNOA on (disaggregated) DuPont components and earnings quality proxies. For each model, yearly cross-sectional regressions are run for the whole subsample. T-statistics for coefficient estimates are computed using the Fama-MacBetch [1973] approach and are additionally adjusted for cross-sectional correlation as suggested by Bernard [1995]. The table also presents the z-statistics from Vuong [1989] tests of differences in explanatory power across the BM and EQ model. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

The BM-Model gives results from standard DuPont analysis without considering earnings quality information. This benchmark model mainly delivers consistent results with prior work. The actual level of RNOA is negative and highly significant which is indicative of mean reversion. The change in ATO is positive and also significant at the 1% level. However, ΔPM is negative and significant in contrast to previous findings (Fairfield and Yohn [2001]; Soliman [2008]). This issue will be discussed in additional analyses (section 5.) in more detail.

By interacting ΔATO and ΔPM with earnings quality proxies, though, previous results distinctively change as reported in the EQ-Model. Whereas the level of current RNOA still delivers highly significant explanatory power without altering the sign of influence, the influence of the change in ATO and PM significantly increases (absolute increase t-value ΔATO: 5.07; absolute increase t-value ΔPM: 3.21). This suggests that ΔATO and ΔPM provide information about the emergence of future changes in RNOA beyond standard DuPont disaggregation. The coefficient on ΔPM appears to bear on confounding influences from the quality of reported numbers in the income statement and, hence, most notably interacts with the conservatism proxy (Q-Score positive and significant at the 5% level). Untabulated analyses reveal that an interaction term between ΔPM, growth and conservatism is highly significant for explaining year-ahead changes in RNOA. This is consistent with findings in Rajan et al. [2007] who claim that conservatism and growth are substitutes in their joint impact on changes in RNOA. Under the influence of conservative accounting, an increase in growth not only has a negative impact on future changes in RNOA, but also magnifies the use of conservative accounting.

The second component of DuPont disaggregation, ΔATO, does not exhibit a statistically significant interaction with the three earnings quality proxies in the in-sample estimation. The growth variable is negative and highly significant in the BM-Model as well as in the EQ-Model. The adjusted-R^2 rises from 3.61% to 3.83% between both models. A Vuong [1989] test compares the explanatory power of the BM-Model and EQ-Model. The earnings quality enhanced forecast model explains future changes in RNOA significantly better than the BM-Model.

Taken together, although after controlling for growth, the consideration of earnings quality increases the explanatory power of the forecast model, even most interactions between earnings quality proxies and DuPont components are not statistically significant. However, traditional DuPont analysis seems not be able to fully capture this effect. To show that this phenomenon not only appears in in-sample estimations, I discuss in the next session whether the consideration of earnings quality leads to improvements in out-of-sample forecasts

4.1.2 Evaluation of out-of-sample prediction

This section documents the usefulness of earnings quality information for predicting one-year-ahead changes in RNOA out-of-sample. I apply the obtained in-sample estimations from yearly cross-sectional regressions to test the accuracy of each model individually and against each other. Table 4 presents summary results on the descriptive statistics of out-of-sample tests. Panel A reports the mean, median and standard deviation of each forecast and of the signed/absolute forecast error. The signed (absolute) forecast error is defined as the (absolute) difference between actual values and the forecast. Panel B documents direct comparisons of the forecasting accuracy between the BM-Model and EQ-Model for each firm-year. I contrast both models from Table 3 in a matched-pair comparison for their absolute forecast errors by evaluating each firm-year from 1996 through 2012. I annually calculate mean and median improvements in prediction accuracy and finally report the grand mean and median values. If the reported value displays a positive sign, the second-mentioned prediction model performs superior in contrast to the first-mentioned model.

Table 4: Statistics on forecasts, forecast errors, and improvements from out-of-sample forecasts for $\Delta RNOA_{t+1}$ (n = 12,478 firm-years / 3,015 firms / 1996 - 2012)

BM-Model: $\Delta RNOA_{t+1,(i)} = \alpha_0 + \beta_1 RNOA_{t,(i)} + \beta_2 \Delta ATO_{t,(i)} + \beta_3 \Delta PM_{t,(i)} + \beta_4 \Delta INT_{t,(i)} + \beta_5 \Delta NOA_{t,(i)} + \varepsilon_{t+1,(i)}$

EQ-Model: $\Delta RNOA_{t+1,(i)} = \alpha_0 + \beta_1 RNOA_{t,(i)} + \beta_2 \Delta ATO_{t,(i)} + \beta_3 \Delta PM_{t,(i)} + \beta_4 \Delta INT_{t,(i)} + \beta_5 \Delta ATO_{t,(i)}*\gamma_{t,(i)} + \beta_6 \Delta ATO_{t,(i)}*\kappa_{t,(i)} + \beta_7 \Delta ATO_{t,(i)}*\pi_{t,(i)} + + \beta_8 \Delta PM_{t,(i)}*\gamma_{t,(i)} + \beta_9 \Delta PM_{t,(i)}*\kappa_{t,(i)} + \beta_{10} \Delta PM_{t,(i)}*\pi_{t,(i)} + \beta_{11} \Delta NOA_{t,(i)} + \varepsilon_{t+1,(i)}$

Panel A: Out-of-sample pooled descriptive statistics

	Forecast			Signed Forecast Error			Absolute Forecast Error		
Model	Mean	Median	STD	Mean	Median	STD	Mean	Median	STD
BM	-0.0189	-0.0159	0.0250	0.0000	0.0131	0.1091	0.0714	0.0464	0.0825
EQ	-0.0174	-0.0154	0.0201	-0.0014	0.0123	0.1087	0.0708	0.0458	0.0825

Panel B: Out-of-sample tests of forecast improvements

	Mean improvement			Median improvement			Number of yearly improvements
Models Compared	Value		*p* value	Value		*p* value	
BM vs EQ	0.0006	**	0.01072	0.0003	**	0.02166	6 / 0

Notes:
Panel A reports the pooled mean, median, and standard deviation for the out-of-sample predictions. Signed forecast errors are the difference between the actual change of RNOA and the predicted change of RNOA. Absolute forecast errors are the absolute errors of the signed forecast errors.

Panel B presents anually grand mean and median improvements in the firm-specific forecast accuracy from out-of-sample prediciton. Forecast accuracy is computed through a matched-pair comparison of absolute forecast errors from two competing models for each firm-year. A positive value for Model A vs B indicates a relative improvement of Model B against Model A. Number of yearly statistically significant improvements are reported on the right side of Panel B. Improvements of models are based on tests of means (median) on Fama-MacBeth t-statistics (Wilcoxon signed rank tests). Number of yearly improvements are based on the yearly median improvements that are significantly positive/negative at the 10% level using two-tailed t-tests. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

The average absolute forecast error is 0.0714 (median 0.0464) for the BM-Model and 0.0708 (median 0.0458) for the EQ-Model. Accordingly, the earnings quality enhanced model distinctively improves the forecast accuracy in both the mean and median. Panel B shows how both prediction models perform in a direct contrast to each other. The improvement of the EQ-Model is significant in the mean and median. In addition, I document the number of yearly improvements or worsening. The EQ-Model significantly outperforms the traditional BM-Model with improvements (worsening) in 6 (0) years.

To deepen the knowledge of the forecast errors, I investigate which coefficients, and to what extent, mainly drive the forecast errors in my prediction models. Table 5 presents results on the association between absolute forecast errors (BM model and EQ model), disaggregated DuPont components, and earnings quality proxies. Since my research question investigates how earnings quality affects DuPont forecasts, I analyze how the explanatory of DuPont components changes after adding earnings quality information to the

prediction models. For this purpose, I use multivariate regression models where absolute forecast errors from both disaggregated DuPont models serve as different dependent variables. To obtain comparability among models, I refer each dependent variable to the same regressors. Hereby, independent variables encompass traditional DuPont components, earnings quality proxies used for in- and out-of-sample predictions, as well as control variables. Multivariate tests (summaries based on the eigenvalues of the regressor matrix from MANOVA), reported at the bottom of Table 5, test the null that all parameters except the intercept are the same for each dependent variable of two models, respectively.

Table 5: Association between disaggregated DuPont coefficients and absolute forecast errors (1996 - 2012)

BM-Model: $AFE(BM\text{-}Model)_{t+1,(i)} = \alpha_0 + \beta_1 RNOA_{t,(i)} + \beta_2 \Delta ATO_{t,(i)} + \beta_3 \Delta PM_{t,(i)} + \beta_4 \Delta INT_{t,(i)} + \sum Controls_{t,(i)} + \varepsilon_{t+1,(i)}$

EQ-Model: $AFE(EQ\text{-}Model)_{t+1,(i)} = \alpha_0 + \beta_1 RNOA_{t,(i)} + \beta_2 \Delta ATO_{t,(i)} + \beta_3 \Delta PM_{t,(i)} + \beta_4 \Delta INT_{t,(i)} + \sum Controls_{t,(i)} + \varepsilon_{t+1,(i)}$

Model	**BM-Model**			**EQ-Model**		
Estimation Method	*Pooled OLS*			*Pooled OLS*		
Dependent Variable	**Absolute forecast error**			**Absolute forecast error**		
Variables	**Coefficients**		**t-statistics**	**Coefficients**		**t-statistics**
Intercept	0.11317	***	4.17	0.11481	***	4.24
$RNOA_t$	0.09705	***	17.26	0.09926	***	17.68
ΔATO_t	-0.04219		-1.38	-0.02709		-0.89
ΔPM_t	0.03472	***	4.32	0.01668	**	2.08
ΔINT_t	0.04200		0.14	0.11612		0.39
Abn. persistenc revenues	-0.00324	***	-2.60	-0.00327	***	-2.63
Abn. persistence NI	-0.00653	***	-5.23	-0.00644	***	-5.18
C-Score	-0.78739		-0.84	-0.90096		-0.96
Q-Score	0.90849		0.96	1.02030		1.08
Growth in NOA	-0.00050		-0.13	-0.00002		-0.01
Size	-0.00476	***	-14.01	-0.00469	***	-13.81
Leverage	0.00004			0.00005	**	1.74
Loss	0.08694	***	44.99	0.08935	***	46.31
Industry Dummies	*Yes*			*Yes*		
Year Dummies	*Yes*			*Yes*		
Firm Years	12,478			12,478		
Unique Firms	3,015			3,015		
Adjusted R^2	22.83%			23.06%		

p- vlaues from multivariate tests
of differences in explanatroy power for the dependent variable

	EQ-Model
BM-Model	0.000 ***

Notes:
This table presents the association between absolute forecast errors from out-of-sample forecasts (see Table 4) and DuPont coefficients. Each model uses forecast errors as dependent variable as they arise from their individual predictions. P-values from multivariate tests examine the hypothesis that all parameters except the intercept are the same for dependent variables of the two models. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

The left side of Table 5 documents results for the benchmark model. Changes in PM (t=4.32) exhibit significant influence on the absolute forecast error. Changes in ATO contribute less to the absolute forecast error (t=-1.38). Persistence in net income and revenues are significant at the 1% level. In direct comparison, the EQ-Model, that interacts DuPont components with earnings quality proxies, reports considerably weaker impact of ΔATO (t = -0.89) and ΔPM (t = 2.08) on explaining prediction errors. These findings suggest that the sole use of disaggregated DuPont components still contributes a significant share to the emergence of forecast errors. It also indicates that the mutual treatment of disaggregated DuPont comments with the control for biases due to changes in earnings quality captures their effect on future profitability more accurately in out-of-sample forecasts. The differences in the explanatory power of the two independent variables for explaining the absolute forecast errors of both models are significant as revealed by the reported multivariate tests. Table 5 also documents that all models fail to predict a future loss as indicated by firms' reported net income in period t+1.

Taken together, the results in Table 4 and 5 are consistent with the predictions of theory: information on earnings quality provides explanatory power for future profitability in in-sample estimations as well as in out-of-sample forecasts.

4.2 Examination of analyst and investor expectation

My preliminary findings suggest that the accuracy of profitability forecasts based on DuPont disaggregation is positively associated with the integration of earnings quality information. In an efficient capital market, I expect the impact of earnings quality on profitability forecasts to be reflected in investors' expectations. In the following section, I examine hypotheses H3 and H4 whether both proxies for market participants, forecasts of financial analysts and market prices, are consistent with the impact of earnings quality on the predictability of future firm performance as stated in my preceding findings.

4.2.1 Analysts' use of earnings quality information for predicting profitability

Previous studies have examined analysts' forecasts as a function of earnings quality in order to shed light of whether this group of market participants incorporates earnings quality attributes in their forecasts (e.g. Elliott and Philbrick [1990], Bhattacharya et al. [2003]). Under the assumption that analysts are unbiased and sufficiently qualified, analysts' forecasts have the advantage relative to stock prices in terms of being an appropriate earnings quality proxy that they relate only to earnings, whereas market prices also reflect other information than earnings (Dechow et al. [2010]). This being the case, I first investigate investors' expectations by examining the association of one-year-ahead earnings predictions from analysts with the out-of-sample forecasts from both types of DuPont disaggregation models that either include or exclude earnings quality information. If analysts effectively incorporate earnings quality information in their prediction models, then their forecasts should be more closely related to the earnings quality enhanced DuPont disaggregation than to the traditional disaggregation.

I use analysts' most recently reported one-year-ahead earnings prediction for period t after the fiscal year-end for year t-1 from the I/B/E/S database from 1996 through 2012. I test analysts' perception towards information of traditional DuPont analysis (BM-Model) as well as towards the earnings quality enhanced models (EQ-Model). These associations are measured via the following regression analysis:

$$Prediciton^{Analysts}\left(\Delta RNOA_{t+1,(i)}\right) = \alpha_0 + \beta_1\, Prediciton^{Model}\left(\Delta RNOA_{t+1,(i)}\right) + \varepsilon_{t+1,(i)}$$

where the dependent variable represents the median consensus forecast of one-year-ahead ΔRNOA from analysts for firm *i* and where the independent variable captures the influence of the two different DuPont disaggregation models, respectively.

Table 6 presents the estimation results for analysts' use of earnings quality information. The findings suggest that the EQ-Model is closer associated to analysts' forecasts than the traditional DuPont disaggregation (BM-Model). With regard to the adjusted-R^2, the EQ-Model explains 13.61% of the variation in analysts' profitability forecasts whereas the BM-Model only reports an explained variance of 11.96%. Tests of differences in the explanatory power across the models (Vuong [1989] test) confirm that the EQ-Model is closer related to analysts' forecasts than the traditional BM-Model. Analysts therefore seem to use earnings quality information for their forecasts as stated in H3.

Table 6: Association between analysts' forecasts and RNOA predictions

Model:	$\text{Predicion}^{\text{Analysts}}(\Delta\text{RNOA}_{t+1,(i)}) = \alpha_0 + \beta_1 \text{Predicition}^{\text{Model}}(\text{RNOA}_{t+1,(i)}) + \varepsilon_{t+1,(i)}$					
Forecast Model	**BM-Model**			**EQ-Model**		
Estimation Method	*Fama-MacBeth regression*			*Fama-MacBeth regression*		
Dependent Variable	**Analysts' RNOA forecast**			**Analysts' RNOA forecast**		
Variables	**Coefficients**		**t-statistics**	**Coefficients**		**t-statistics**
Intercept	0.0746	***	10.67	0.0666	***	7.22
Forecast by Model	-2.1624	***	-6.86	-2.6037	***	-12.50
Standard Errors	*Newey-West adjusted*			*Newey-West adjusted*		
Truncation	*1% level from both sides*			*1% level from both sides*		
Firm Years	7,853			6,846		
Unique Firms	1,951			1,750		
Adjusted R^2	11.96%			13.61%		

Differences in adjusted-R^2
Vuong test (Z-statistic)

	BM-Model	EQ-Model
BM-Model	-	-
EQ-Model	-3.81***	-

Notes:
The sample consists of firm-year observations from 1996 - 2012. Regressions are estimated annually using the Fama-MacBeth [1973] approach of cross-sectional regressions for all firms (17 years). t-statistics are calculated as suggested by Bernard [1995]. The table also presents the z-statistics from Vuong [1989] tests of differences in explanatory power across the BM and EQ model. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

4.2.2 Investors use of earnings quality information for predicting profitability

Since the previous section found that analysts seem to be aware of earnings quality information for predicting future changes in profitability, investors also may find this set of information valuable. For investigating the awareness of the stock market, I define two mechanical trading rules that may exploit investors' inefficient use of earnings quality information. I follow Berger and Hann [2003] and Fairfield et al. [2009] which suggest an approach to examine the accuracy of two competing models by examining the abnormal returns to three groups of portfolios (long, short, and hedge portfolio formation strategies). If market participants efficiently include earnings quality information in their decision making process, then buying (short-selling) stocks of firms where the earnings quality enhanced models predict higher (lower) changes in one-year-ahead changes in RNOA than the traditional DuPont model should generate abnormal returns. Stock data are obtained from the Center of Research in Security Prices (CRSP). Abnormal returns are calculated for a 12-month buy-and-hold period, beginning from the fourth month of year t until the third month after fiscal year-end t+1. Market returns for the corresponding month are calculated on the basis of value-weighted returns of the total population of the data sample.

The results are presented in Table 7. Returns from the long side are on average positive over the entire sample period and also predominantly positive on a fiscal year basis. However, stocks from the short-selling portfolios mostly generate negative returns.[*] After summing up the long and short portfolios, hedge returns are slightly negative, but not statistically different from zero. I can therefore not reject the hypothesis that investors use earnings information efficiently in predicting future changes in profitability with DuPont analysis. This test undergoes a quite simple trading heuristic, though, and leaves much room for improvement.

[*] It may apply that the data selection process excluded several bad performing firms so that the underlying sample underlies a "winner bias". As a result, short-selling might not be an appropriate strategy having a right skewed return distribution.

Table 7: Analysis of stock returns based on traditional DuPont analysis and earnings quality enhanced predictions - twelve-month abnormal returns of trading rule portfolios

	Portfolio
Long:	$\text{Prediction}^{\text{BM-Model}}(\Delta\text{RNOA}_{t+1,(i)}) < \text{Prediction}^{\text{EQ-Moel}}(\Delta\text{RNOA}_{t+1,(i)})$
Short:	$\text{Prediction}^{\text{BM-Model}}(\Delta\text{RNOA}_{t+1,(i)}) > \text{Prediction}^{\text{EQ-Moel}}(\Delta\text{RNOA}_{t+1,(i)})$

Strategy	N	12-month BHAR	p-Value
Hedge portfolio	4,027		
Years positive / negative	9 / 8		
Mean return		-1.37%	0.281
Median return		-0.31%	0.768
Long portfolio	2,033		
Years positive / negative	12 / 5		
Mean return		6.07%	0.220
Median return		4.91%	0.311
Short portfolio	1,994		
Years positive / negative	5 / 12		
Mean return		-7.44%	0.145
Median return		-5.21%	0.288

Notes:
This table presents the distribution of 12-month abnormal returns for a trading portfolio based on two prediction models using DuPont disaggregation (BM and EQ). The return cumulation period begins in the fourth month of each fiscal year and extends into the third month after the end of each fiscal year.The sample consists of firm-year observations from 1996 – 2012.

The 12-month abnormal buy-and-hold abnormal returns (book-to-market matched control firms) is computed as:

$$\prod_{m=1}^{m=12}\left(1+R_{i,m}\right)-\prod_{m=1}^{m=12}\left(1+VWR_{m}\right)$$

where $R_{i,m}$ is the monthly return of firm i, and VWR_m is the value-weighted return for the corresponding month. See Berger and Hann [2013] for further details.

5. Additional analyses and robustness tests

I subject my results to a battery of additional analyses as well as robustness and specification tests in untabulated analyses. Prior research raises the possibility that systematic inter-industry differences affect the accuracy of forecast models. To investigate the robustness of my results to this issue, I run in-sample and out-of-sample forecasts for firm groups within two-digit as well as four-digit GICS industry sectors obtained from COMPUSTAT. The EQ-Model outperforms the BM-Model in both industry specifications. Consistent with Fairfield et al. [2009], the results from the economy-wide forecasts lead to better results in predicting future profitability than the industry-specific models.

When conducting the in-sample estimation with rolling regressions, I observe that the actual change in PM exhibits significant explanatory power for one-year-ahead changes in RNOA. In contrast, previous research reports that ΔPM is not incremental useful for predicting $\Delta RNOA_{t+1}$ by using yearly cross-sectional regressions. To evaluate that this difference is due to a different econometrical forecast approach rather than driven by different sample firms or changes over time, I calculate the in-sample coefficients for the BM-Model as well as the EQ-Model with yearly cross-sectional regressions. Inconsistent with prior findings, ΔPM is negative and still significant. An inspection of yearly estimated coefficients reveals that the explanatory of ΔPM increasingly raises over the past decade. My previous results concerning the influence of firms' earnings quality for predicting profitability stay stable. Additionally, I test whether the rolling regression or the cross-sectional based forecast perform better. In the grand mean and median, rolling regression-based forecasts beat cross-sectional forecasts. However, the rolling regression is not superior on an annual level since it doesn't improve the forecast on a statistically significant level in a single year.

Last, I expand the proxies for conservative accounting as suggested by Penman and Zhang [2014]. I find that altering the definition of the C-Score and Q-Score does not affect my results.

6. Conclusion

This paper tests how the reporting quality of earnings affects the accuracy of ratio-based forecast models. I combine distinct findings from both literature streams, earnings quality research and financial statement analysis literature, to test their mutual impact on profitability forecast models. Adding earnings quality information to ratio-based forecasts provides incremental information over standard DuPont disaggregation, including the level of current RNOA and growth in net operating assets, as suggested in prior studies. I provide evidence that the explanatory power of in-sample estimations increases and that the forecast accuracy of out-of-sample forecasts improves.

My results provide researchers and practitioners with a parsimonious method for adjusting FSA forecasts to the bias through contemporaneous changes in the quality of reported earnings. However, by analyzing the association between earnings quality enhanced forecast models and analysts as well as stock market investors, I show that both market participants impound earnings quality information in their decisions. This result raises the question of how and to what extent market participants use earnings quality information. Further, future research could test whether markets therefore exclusively draw on financial statement information or whether other public or private sources provide information about the influence of earnings quality on firms' future performance.

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Appendix 1

Variable definitions

Variable	Description	Computation
CEQ_t	Common equity	
CHE_t	Cash and short-term investments	
DLC_t	Debt in current liabilities	
$DLTT_t$	Long-term debt	
DO_t	Discontinued operations	
DVP_t	Dividends preferred	
$DVPA_t$	Dividends preferred in arrears	
$IDIT_t$	Interest and related income	
$IVAO_t$	Other investments and advances	
$LIFR_t$	LIFO reserves	
NI_t	Net income	
$PSTK_t$	Preferred stock	
$REVT_t$	Revenues	
TXT_t	Income taxes	
$TSTKP_t$	Preferred treasury stock	
XAD_t	Advertising expenses	
XRD_t	Research and developement expenses	
CSE_t	Common shareholders' equity	$CEQ_t + TSTKP_t - DVPA_t$
FA_t	Financial assets	$CHE_t + IVAO_t$
FO_t	Financial obligations	$DLC_t + DLTT_t + PSTK_t - TSTKP_t + DVPA_t$
NFE_t	Net financial expenses	$-(IDIT_t - XINT_t - DVP_t)$
NFO_t	Net financial assets	$FO_t - FA_t$
$NIBT_t$	Net income before taxes	$NI_t + TXT_t - DVP_t - DO_t$
NOA_t	Net operating assets	$FO_t - FA_t + CSE_t$
NOI_t	Net operating income	$NIBT_t + NFE_t$
$ANFO_t$	Average net financial obligations	$(NFO_t + NFO_{t-1}) / 2$
$ANOA_t$	Average net operating assets	$(NOA_t + NOA_{t-1}) / 2$
ATO_t	Asset turnover	$REVT_t / ANOA_t$
BVE_t	Average common shareholders' equity	$(CSE_t + CSE_{t-1}) / 2$
LEV_t	Leverage	$ANFO_t / BVE_t$
NBC_t	Net borrowing costs	$NFE_t / ANFO_t$
PM_t	Profit margin	$NOI_t / REVT_t$
$RNOA_t$	Return on net operating assets	$NOI_t / ANOA_t$
ΔATO_t	Change in asset turnover	$((ATO_t - ATO_{t-1}) / ATO_{t-1}) \times PM_{t-1}$
ΔINT_t	Interaction between change in asset turnover and change in profit margin	$\Delta ATO_t \times \Delta PM_t$
ΔNOA_t	Change in net operating assets	$(NOA_t - NOA_{t-1}) / NOA_{t-1}$
ΔPM_t	Change in profit margin	$((PM_t - PM_{t-1}) / PM_{t-1}) \times ATO_{t-1}$
$\Delta RNOA_t$	Change in return on net operating assets	$(RNOA_t - RNOA_{-1}) / RNOA_{t-1}$

Teil 5

Determinanten und Beständigkeit extremer Ergebnisprognosefehler von Finanzanalysten - Eine bilanzkennzahlenorientierte Analyse europäischer Unternehmen

Matthias Demmer*

Abstract

A great body of capital market research investigates forecast errors of financial analysts for years. In some cases, forecast errors exhibit an extensive dispersion of several hundred percent error rates. However, so-called “extreme” forecast errors are often excluded from empirical research for the sake of statistical validity. In order to bridge the gap within this literature stream, the upcoming article explicitly focuses on such extreme forecast errors and sheds light on this insufficiently noticed research topic. By examining a comprehensive data sample of European firms (over 20,000 firm year observations) and analysts’ forecasts (over 140,000), the article empirically investigates firm characteristics based on a wide range of disclosure information. The analysis shows that firms with high forecast dispersion tend to operate in a volatile market environment. Additionally, they are more likely to face fluctuations in profitability. Likewise, analysts do not appear adjusting forecasts efficiently in the year after an extreme estimation error. This specifically applies to highly overrated firms.

Keywords

Analysten, Ergebnisprognosefehler, extreme Schätzfehler, Jahresabschlussanalyse, Bilanzkennzahlen

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1. Einleitung

Ergebnisprognosen entstehen durch die Tätigkeit von Analysten als Informationsintermediäre, welche aus einem komplexen Spektrum an Informationsquellen ökonomische Beurteilungen ableiten. Sie dienen mitunter als Entscheidungsgrundlage für Kapitalmarktteilnehmer.[1] Zum Beispiel werden Ergebnisprognosen als Komponenten in zahlreichen weiterführenden Anwendungsbereichen der Kapitalallokation oder in Bewertungsmodellen von Unternehmen verwendet. Allerdings wurde der Nutzen von Ergebnisprognosen durch überoptimistische Kaufempfehlungen und nicht vorhergesehene Spekulationsblasen (z.B. Dot-Com-Krise, Finanzkrise) in öffentlich geführten Diskussionen in letzter Zeit zunehmend in Frage gestellt.[2] Auch im wissenschaftlichen Umfeld der Kapitalmarktliteratur ist die Ergebnisprognose durch den Analysten ein intensiv untersuchtes Forschungsfeld. Gerade in den letzten zwanzig Jahren wurde eine Vielzahl empirischer Studien veröffentlicht, welche unter anderem die Ergebnisgüte (bzw. den Ergebnisprognosefehler) von Analysten analysieren.[3] Diese Studien lassen sich grobgliedrig danach unterscheiden, ob Zusammenhänge zwischen Ergebnisprognosefehlern und Analysteneigenschaften (z.B. Erfahrung, Umfeld etc.) oder zwischen Ergebnisprognosefehlern und Unternehmenseigenschaften (z.B. Untersuchung diverser Firmencharakteristika) untersucht werden. Dabei zeigt sich, dass die Stärke bzw. das Ausmaß des Ergebnisprognosefehlers sehr unterschiedlich ausfällt. D.h. der Ergebnisprognosefehler von Analysten ist durch eine hohe Streuung charakterisiert. So sind Prognosefehler des Jahresergebnisses (meistens gemessen an sog. Earnings per Share – EPS[4]) mit weit über 100% Abweichung keine Seltenheit. Die extremen Abweichungen von der ursprünglichen Ergebnisprognose können statistische Testverfahren verzerren, wodurch eine Vielzahl von empirischen Untersuchungen diese zur Erhöhung der Güte des Schätzmodells ausschließt. Indes ist gerade ein Verständnis der extremen Ergebnisprognosefehler für die in der Realität agierenden Kapitalmarktteilnehmer interessant, da diese ein hohes ökonomisches Risiko mit sich tragen können. In Anbetracht dieser Tatsache ist es erstaunlich, dass extremen Ergebnisprognosefehlern in empirischen Analysen bisher kaum Beachtung geschenkt wurde.

Daher verfolgt dieser Artikel das Ziel, extreme Ergebnisprognosefehler und ihre Entstehung sowie Beständigkeit in Folgejahren zu analysieren. Der Untersuchungsrahmen umfasst 17 europäische Länder über einen Zeitraum von zwölf Jahren (2000-2012). Mittels

[1] Vgl. Oberdörster (2009), S. 57 f.
[2] Vgl. z.B. Braunberger (2010).
[3] Einen guten Literaturüberblick gibt z.B. Ramnath et al. (2008).
[4] Im deutschen Schrifttum wird hier oftmals alternativ der Begriff Gewinn je Aktie verwendet.

einer bilanzkennzahlenorientierten Analyse wird analysiert, welche Unternehmenscharakteristika mit extremen Ergebnisprognosefehlern assoziiert sind, um Rückschlüsse auf die Determinanten einer erschwerten Ergebnisprognose zu ziehen. Darüber hinaus wird untersucht, wie sich die Genauigkeit von Ergebnisprognosen vor bzw. nach dem extremen Schätzfehler verhält. Hierdurch soll abgeleitet werden, ob Analysten ihre Ergebnisprognosen in Folge eines Schätzfehlers hinreichend adjustieren.

2. Ergebnisprognosen und bisherige Erkenntnisse zu Ergebnisprognosefehlern

2.1. Ergebnisprognosen von Finanzanalysten und deren institutionelles Umfeld

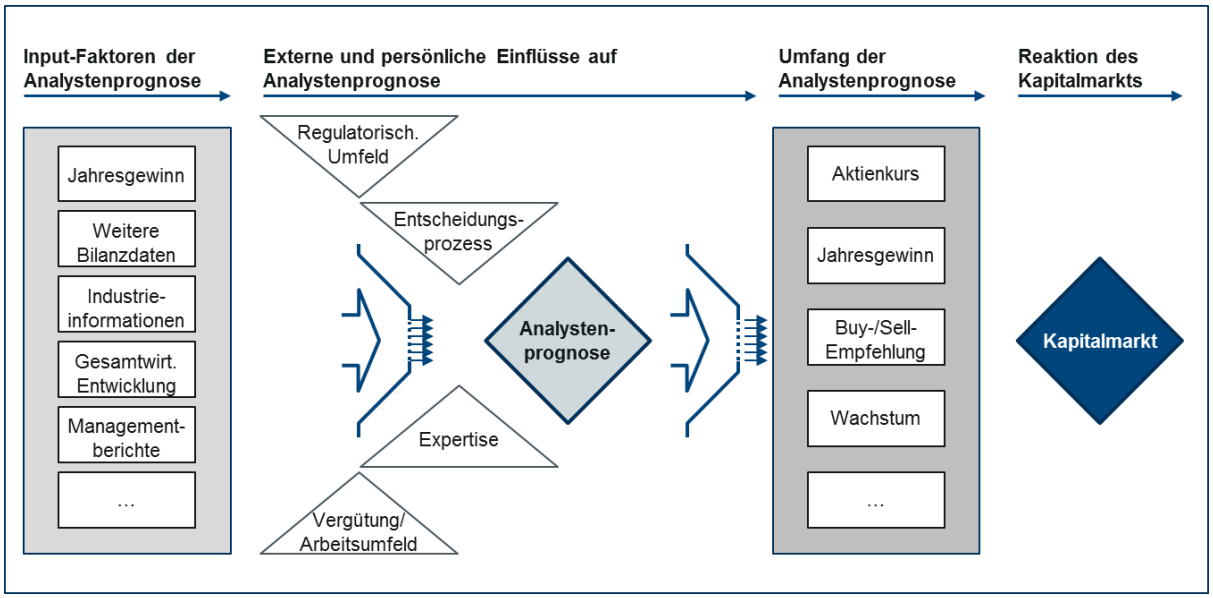
Ergebnisprognosen werden durch eine Vielzahl persönlicher und exogener Einflussfaktoren bestimmt. Bisherige Forschungsergebnisse umfassen eine breite Palette an potentiellen Einflüssen. Es werden nicht nur die Prognosen selbst untersucht, sondern ebenso deren determinierendes Umfeld und die daraus resultierenden Implikationen. Die wissenschaftliche Forschung bezüglich der Entstehung und Wirkung von Analystenergebnisprognosen lässt sich in fünf Themenblöcke unterteilen (siehe Abbildung 1).[5]

Der erste Block thematisiert Input-Faktoren für Prognosen. Untersuchungsgegenstand ist primär die Auswertung unterschiedlicher Informationsquellen von Analysten und inwieweit diese die Prognosegenauigkeit beeinflussen. Darauf werden im zweiten Block das Analystenumfeld und die regulatorischen Rahmenbedingungen der zu Verfügung stehenden Informationen beleuchtet. Dieser Block widmet sich ebenso den Analysten selbst und deren unmittelbarem Umfeld. Hier werden vorrangig personelle Attribute (z.B. individuelle Expertise oder Branchenspezifizierung etc.) und Arbeitsabläufe von Analysten untersucht. Dabei werden wie beim ersten Block Rückschlüsse gezogen, inwieweit sich persönliche Attribute eines Analysten auf die Schätzgenauigkeit unterschiedlicher Prognoseobjekte (Block 3, z.B. Jahresergebnis, Aktienkurs etc.) auswirken. Zuletzt werden die Prognosen in Verbindung zum Kapitalmarkt gesetzt, indem Einflüsse von Prognosen auf Marktteilnehmer analysiert werden und unterschiedliche Reaktionen durch veröffentlichte Analysteneinschätzungen getestet werden. Diese Simplifizierung umfasst den Entstehungs-

[5] Vgl. Ramnath et al. (2008), S. 37.

und Wirkungszyklus von Analystenprognosen und zeigt zugleich Stellhebel auf, wie und wo die Genauigkeit einer Ergebnisprognose beeinflusst werden kann.

Abbildung 1: Das Prognoseumfeld von Analysten[6]



2.2. Bisherige Erkenntnisse zu Ergebnisprognosefehlern

Der wichtigste Forschungszweig im Bereich des Untersuchungsfeldes von Analysten geht der Frage nach, welche Faktoren die Schätzgenauigkeit der Prognosen beeinflussen. Bisherige Studien untersuchen eine Vielzahl potentieller Einflussgrößen und Störterme. Der folgende Abschnitt umreißt wichtige Erkenntnisse ohne dabei Anspruch auf Vollständigkeit zu erheben.

So wurde unter anderem festgestellt, dass Analysten neben Bilanzzahlen auch eine Vielzahl an qualitativen Informationen aus Jahresabschlüssen und weiteren Quellen verwenden.[7] Der Prognosefehler korreliert stark mit der Qualität der Bilanzinformationen.[8] Auch Umweltfaktoren des bewerteten Unternehmens schlagen sich auf den Prognosefehler nieder. Beispielsweise sinkt die Prognosegenauigkeit mit dem Grad an internationaler Diversifizierung des Unternehmens[9] oder unmittelbar nach Unternehmenstransaktionen

[6] In Anlehnung Ramnath et al. (2008), S. 37.
[7] Vgl. z.B. Rogers und Grant (1997), S.17-30.
[8] Vgl. z.B. Lang und Lundholm (1996), S. 467-492.
[9] Vgl. z.B. Duru und Reeb (2002), S. 415-433.

(M&A).[10] Zudem können diverse weitere Unternehmenscharakteristika wie Firmengröße, Kapitalstruktur oder Gewinnvolatilität die Prognose von Analysten beeinflussen.[11]

Ein weiterer zentraler Forschungsansatz ist die Expertise der Analysten sowie die Professionalität ihres Arbeitgebers. Nach diesen Studien steigt die Qualität der Prognose mit einer Industrie- oder Firmenspezialisierung des Analysten.[12] Auch die Größe des Arbeitgebers ist entscheidend (z.B. auf Grund eines besseren Informationszugangs). Hingegen wird die reine Erfahrung gemessen an Berufsjahren als nicht entscheidend für die Güte einer Prognose gesehen.[13] Interessant in diesem Zusammenhang ist auch das sog. „herding". Darunter wird verstanden, dass Analysten sich an Prognosen ihrer Kollegen orientieren, um im Falle eines hohen Prognosefehlers nicht deutlich aus dem Kollektiv herauszustechen. Meist werden persönliche Karrieregründe und Mangel an öffentlich zur Verfügung stehenden Informationen über eine Firma für dieses Verhalten aufgeführt.

Obwohl Ergebnisprognosen durchschnittlich besser sind als rein statistische Zahlenmodelle oder gar naive Prognosemodelle (z.B. zufällige Random-Walk-Prognosen)[14], kann nachgewiesen werden, dass Analysten oftmals irrational auf gewisse Informationen oder Marktstimmungen reagieren. So beurteilen Analysten sehr gute und sehr schlechte Neuigkeiten asymmetrisch. Überwiegend geht man davon aus, dass ein Optimismus gegenüber guten Neuigkeiten und eine Unterreaktion gegenüber schlechten Neuigkeiten die Überschätzung von Analysten signifikant bestimmt.[15] Als Resultat entsteht eine systematische Überschätzung von Ergebnissen. Allerdings wird kontrovers diskutiert, welche weiteren Faktoren diese Asymmetrie beeinflussen. Zudem scheinen Analysten manche Informationen nicht effizient zu verarbeiten. So können beispielsweise diskretionäre Periodenabgrenzungen (Accruals) oder transitorische Gewinn- oder Kostenkomponenten (z.B. außerordentliche Erträge oder Sonderabschreibungen) die Höhe von Ergebnisprognosefehlern statistisch erklären. Ebenso werden fundamentale Bilanzkennzahlen, wie z.B. Verschuldungsgrad, Eigenkapitalquote, Umsatzwachstum etc. herangezogen, um deren Zusammenhang mit der Ergebnisprognose von Analysten zu untersuchen.[16]

Im Gegensatz zu den oben genannten Beurteilungsfehlern durch selektive oder gar fehlerhafte Wahrnehmung von Informationen, untersucht die Literatur auch diverse

[10] Vgl. z.B. Haw et al. (1994), S. 465-483.
[11] Vgl. z.B. Mikhail et al. (2003), S. 101-116.
[12] Vgl. z.B. Clement (1999), S. 285-303.
[13] Vgl. z.B. Jacobet al. (1999), S.51-82.
[14] Vgl. z.B. Walther (1997), S. 157-179.
[15] Vgl. z.B. Easterwood und Nutt (1999), S. 1777-1797.
[16] Vgl. z.B. Lev und Thiagarajan (1993), S. 190-215.

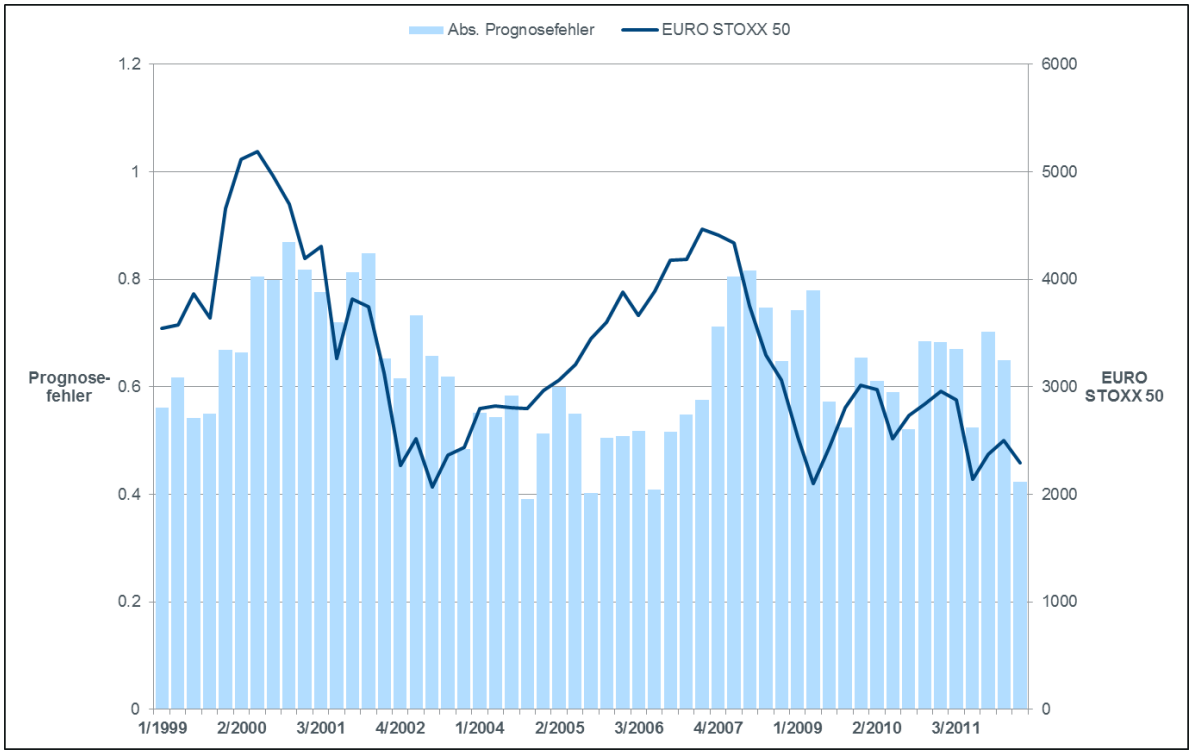
persönlich bedingte Interessenskonflikte von Analysten. Oftmals werden hierfür Principal-Agency-Probleme aufgeführt. Die daraus resultierenden Interessenskonflikte werden als maßgeblicher Grund für die Entstehung von Prognosefehlern herangezogen. Gerade geschäftliche Beziehungen zwischen Analysten und dem zu bewertenden Unternehmen sind sowohl im wissenschaftlichen als auch im öffentlichen Umfeld kontrovers diskutiert worden. Marktteilnehmer erwarten von Analysten unvoreingenommene Beurteilungen. Jedoch kann der Arbeitgeber des Analysten gleichwohl andere geschäftliche Beziehungen mit dem zu bewertenden Unternehmen haben (z.B. in Bereichen des Commercial oder Investment Bankings). Ebenso ist es im Sinne eines Analysten, Beziehungen zum Unternehmensmanagement aufzubauen, um Zugang zu internen Informationen zu erhalten. Eine für das Unternehmen schlechte Prognose würde solche Beziehungen torpedieren.[17] Aus diesem Zielkonflikt resultiert die sogenannte „Earnings-Game-Theorie".[18] Diese unterstellt einen strategischen Anpassungsprozess von Analysten und deren Prognosen. Dabei werden zunächst optimistisch ausgewiesene Prognosen bei näher rückendem Veröffentlichungszeitpunkt des geschätzten Firmenwertes nach unten revidiert, sodass das Unternehmen die Analystenerwartung knapp übertreffen kann. Somit soll eine positive Reaktion des Kapitalmarktes stimuliert werden.

Zuletzt ist noch das rechtliche, regulatorische und makroökonomische Umfeld zu nennen, das teils indirekt, aber auch direkt die Prognosegenauigkeit beeinflusst. So werden die jeweiligen Rechnungslegungsstandards, rechtliche und wirtschaftliche Rahmenbedingungen[19] (z.B. Korruption, nationale Gesetzesvorschriften etc.) oder auch strukturelle Krisen[20] (z.B. Finanzkrise) im Hinblick auf Prognosefehler von Analysten untersucht.

Diese kompakte Literaturübersicht verdeutlicht, dass Ergebnisprognosen durch die unterschiedlichsten Einflüsse determiniert werden können. Dementsprechend volatil verlief die durchschnittliche Ergebnisprognosegenauigkeit über die letzten 15 Jahre (siehe Abbildung 2). Der durchschnittliche, absolute Ergebnisprognosefehler für europäische Firmen lag zwischen 39% und 92%.

[17] Vgl. z.B. Francis und Philbrick (1993), 216-230.
[18] Vgl. z.B. Chopra (1998), S. 35-42.
[19] Vgl. z.B. Barniv et al. (2005), S. 727-758.
[20] Vgl. z.B. Hsu et al. (2013), S. 673-682.

Abbildung 2: Verlauf des absoluten Prognosefehlers europäischer Unternehmen[21] gegenüber der Entwicklung des EURO STOXX 50



3. Analyse der Unternehmenscharakteristika als Determinanten extremer Ergebnisprognosefehler

3.1. Datenbasis

Die nachfolgende empirische Untersuchung umfasst Unternehmen und deren Ergebnisprognosen von Analysten aus 17 europäischen Ländern über den Zeitraum der Jahre 2000 bis 2012. Ergebnisprognosen sind der Datenbank *Institutional Brokers' Estimate System* (I/B/E/S) entnommen. Dieselben Auswahlkriterien wurden für europäische Unternehmen (exklusive Finanzinstitute) definiert, um detaillierte Bilanzinformationen[22] aus der *COMPUSTAT Global Vantage* Datenbank zu extrahieren. Die Schnittmenge beider Datensätze bildet das finale Datensample der Studie. Dieses enthält 141.678 Ergebnisprognosen sowie 20.881 Unternehmensbeobachtungen (vgl. Tabelle 1). Sowohl für die Anzahl an Ergebnisprognosen, als auch für die Anzahl an korrespondierenden Unternehmensbeobachtungen ist ein deutlicher Anstieg über den Untersuchungszeitraum festzustellen. Die Auswirkungen der Finanzkrise sind deutlich durch sinkende

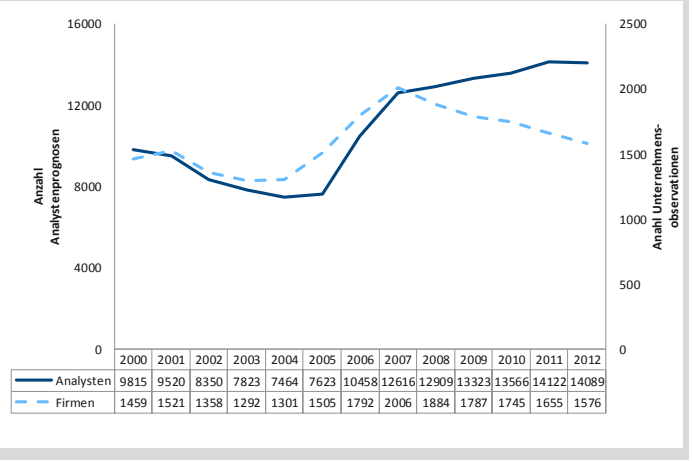
[21] Die Grafik wertet alle in I/B/E/S verfügbaren Ergebnisprognosefehler (521.218) vom 1.Quart.1999 - 3.Quart. 2012 aus. Tabelle 1 gibt eine Übersicht über die analysierten Länder.
[22] Bilanzinformationen stammen ausschließlich aus dem Jahresabschluss.

Unternehmensobservationen ab 2007 zu erkennen (Abbildung 3).[23] Insolvenzen, Delistings (Börsenabgänge) und Unternehmensfusionen senken die jährlichen Unternehmensobservationen von 2007 bis 2012 um ca. 21%. Unternehmen aus Großbritannien, Frankreich und Deutschland repräsentieren insgesamt etwa die Hälfte der Observationen im Datensatz.

Tabelle 1: Anzahl und Anteil an Ergebnisprognosen und Unternehmensobservationen der empirischen Untersuchung pro Land

	Analysten-prognosen		*Unternehmens-observationen*	
Land	**Anzahl**	**Anteil**	**Anzahl**	**Anteil**
Belgien	3,783	2.67%	617	2.95%
Dänemark	3,835	2.71%	596	2.85%
Deutschland	20,213	14.27%	2,551	12.22%
Finnland	7,037	4.97%	894	4.28%
Frankreich	20,557	14.51%	2,484	11.90%
Griechenland	2,958	2.09%	514	2.46%
Großbritannien	30,055	21.21%	5,944	28.47%
Irland	1,190	0.84%	226	1.08%
Italien	10,204	7.20%	1,346	6.45%
Niederlande	6,557	4.63%	623	2.98%
Norwegen	5,070	3.58%	913	4.37%
Österreich	1,777	1.25%	294	1.41%
Polen	1,892	1.34%	424	2.03%
Portugal	1,680	1.19%	254	1.22%
Schweden	7,605	5.37%	1,307	6.26%
Schweiz	7,887	5.57%	1,081	5.18%
Spanien	9,378	6.62%	813	3.89%
Total	141,678	100%	20,881	100%

Abbildung 3: Anzahl an Ergebnisprognosen und Unternehmensobservationen von 2000-2012



3.2. Identifizierung extremer Ergebnisprognosefehler

Die Studie unterteilt Prognosefehler von Analysten in drei Gruppen:

1. Extreme Überschätzer
2. Extreme Unterschätzer
3. Durchschnittliche Prognosefehler (Vergleichsgruppe)

Dabei wird der jeweilige Ergebnisprognosefehler für ein Unternehmen wie folgt berechnet:[24]

$$P_{i,t}^{error} = \frac{EPS_{i,t}^{Actual} - EPS_{i,t}^{Forecast}}{\left| EPS_{i,t}^{Forecast} \right|}$$

[23] Vgl. hierzu z.B. Folkinshteyn und Meric (2014), S. 1-16.
[24] Für alternative Berechnungsmöglichkeiten siehe z.B. Byard et al. (2011), S. 69-96.

mit:

$P_{i,t}^{error}$: Prognosefehler für Firma *i* zum Zeitpunkt *t*

$EPS_{i,t}^{Actual}$: Im Jahresabschluss ausgewiesene EPS (earnigs per Share) von Firma *i* zum Zeitpunkt *t*

$EPS_{i,t}^{Forecast}$: Durchschnittliche Ergebnisprognose[25] der EPS für Firma *i* für den Jahresabschluss im Jahr *t* [26]

Folglich entsteht ein Überschätzer, wenn Analysten die erwarteten Gewinne je Aktie eines Unternehmens zu hoch prognostizieren ($P_{i,t}^{error}$ hat somit ein negatives Vorzeichen). Hingegen entsteht ein Unterschätzer, wenn das Unternehmensergebnis die Ergebnisprognose übertrifft (positives Vorzeichen).

Anschließend werden Unternehmensbeobachtungen mit extremen Ergebnisprognosefehlern ihren jeweiligen Gruppen zugeordnet. Hierfür werden die Prognosefehler in Perzentile unterteilt.[27] Die Schätzfehlergruppen werden wie folgt definiert:[28]

1. Extreme Überschätzer < Zehntes Perzentil ($P^{0.1}$)
2. Extreme Unterschätzer > Neunzigstes Perzentil ($P^{0.9}$)
3. Neunzigstes Perzentil ($P^{0.9}$) ≥ Vergleichsgruppe ≥ Zehntes Perzentil ($P^{0.1}$)

Abbildung 4 betrachtet den Verlauf der drei Prognosefehlergruppen über den Untersuchungszeitraum. In Übereinstimmung mit bisherigen Erkenntnissen sind Ergebnisprognosen im Durchschnitt zu positiv.[29] Der Schätzfehler der Vergleichsgruppe liegt im Durchschnitt bei -20% (-6% Median). Der durchschnittliche extreme Unterschätzer ist durchweg positiv (Fehlprognose ca. +64%). Die extremen Überschätzer von Analysten haben über -250% Abweichung vom eingetretenen EPS. Hierbei besitzen die extremen Prognosefehler eine sichtbare temporäre Stabilität, die selbst während der Finanzkrise anhält. Während als normal definierte Analystenfehler zyklischen Schwankungen unterliegen, bleiben extreme Unter- bzw. Überschätzer relativ stabil. Obwohl der absolute Prognosefehler steigt (vgl. Abbildung 2), sinkt der Optimismus in der Vergleichsgruppe.

[25] Die durchschnittliche Ergebnisprognose ist der Consensus Forecast aus I/B/E/S, der jeweils den Mittelwert/Median aller Prognosen eines Unternehmens umfasst. Die Studie berechnet den Prognosefehler sowohl auf Basis des Mittelwertes, als auch auf Basis des Medians.

[26] Verwendet wird die „most recent" Ergebnisprognose, d.h. im Falle mehrerer Prognosen eines Analysten während eines Bilanzjahres wird die jeweils aktuellste Prognose verwendet.

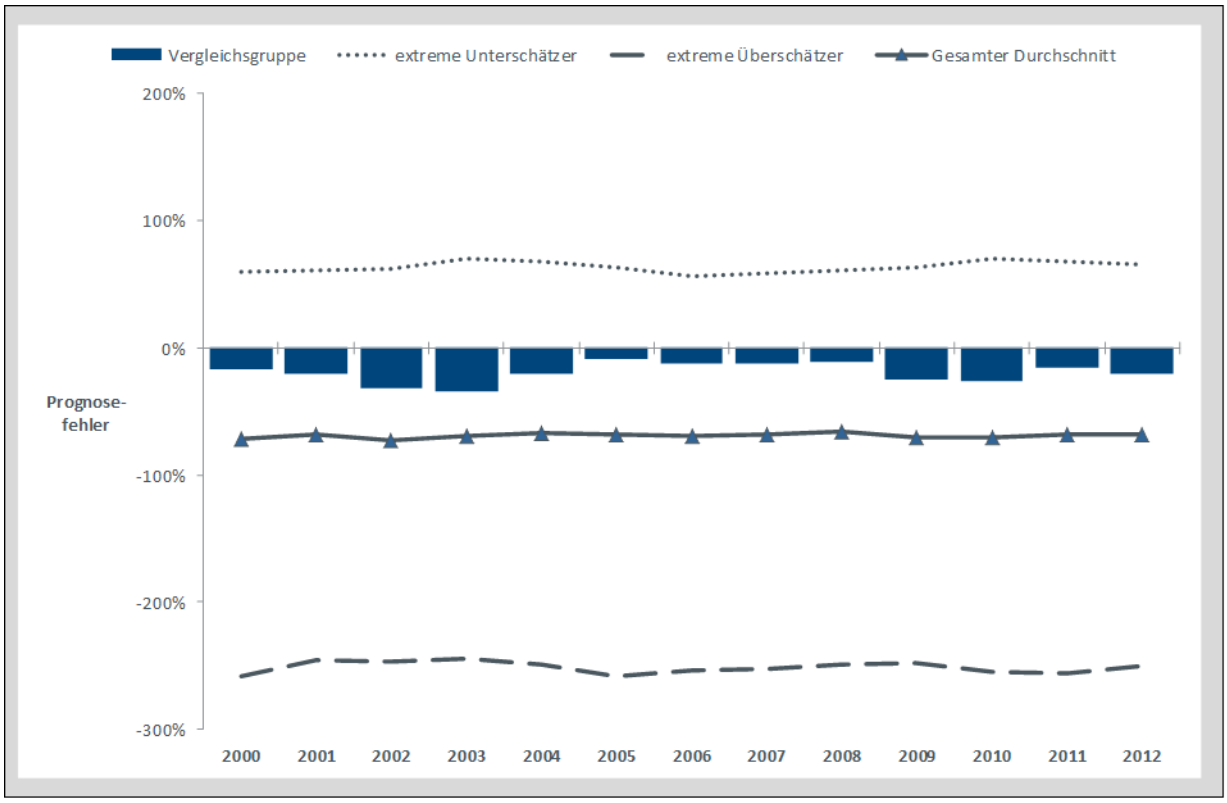
[27] Es ist anzumerken, dass die Einteilung der Ergebnisprognosefehler in die verschiedenen Kategorien willkürlich geschieht. Alternativ wäre auch eine Einteilung in Quartile oder Quintile bzw. die Festlegung extremer Ergebnisprognosefehler innerhalb des 1%- bzw. 99%-Perzentils denkbar.

[28] Die Gruppen werden jedes Jahr neu zusammengestellt. Folglich werden alle Observationen pro Jahr in Perzentile unterteilt. Liegt das neunzigste Perzentil beispielsweise in einem Jahr bei +60% Ergebnisprognosefehler, werden alle Beobachtungen über 60% als extreme Unterschätzer definiert.

[29] Vgl. z.B. Dechow et al. (2000), S. 1-32.

Analysten scheinen in Zeiten struktureller Depressionen ihren Optimismus zu reduzieren und verschieben den Fokus ihrer Prognosen vermutlich auf andere Informationskanäle (z.B. durch vermehrten Einsatz von Fundamentalanalysen oder makroökonomischen Indikatoren).

Abbildung 4: Zeitlicher Verlauf extremer Prognosefehler gegenüber der Vergleichsgruppe



3.3. Identifizierung extremer Ergebnisprognosefehler

Für die folgenden deskriptiven Auswertungen in Tabelle 2 und 3 werden grundlegende Eckdaten der Aktiv- und Passivseite der Unternehmensbilanz, der GuV-Rechnung sowie der Kapitalflussrechnung beleuchtet. Die deskriptiven Auswertungen für Firmen mit extremen Schätzfehlern werden separiert ausgegeben. Für jede Bilanzkennzahl wurden Lage- und Streuungsmaße pro Gruppe berechnet. Insbesondere innerhalb der Gruppen mit extremen Schätzfehlern herrscht eine starke Heterogenität. Demzufolge weisen fehlgeschätzte Unternehmen kein eindeutiges Unternehmensprofil hinsichtlich allgemeiner Unternehmenseigenschaften auf. Allerdings zeichnen sich signifikante Unterschiede zwischen den drei Gruppen ab. Dabei wird mittels statistischer Testverfahren[30] auf

[30] Hierfür wurde zunächst die jeweilige Wahrscheinlichkeitsverteilung einer Kennzahl bestimmt, um anschließend mittels zweiseitiger parameterfreier oder t-verteiler Homogenitätstests auf Gruppenunterschiede zu prüfen.

Unterschiede zwischen den drei Gruppen (extreme Überschätzer, extreme Unterschätzer und normale Prognosefehler) getestet.

Tabelle 2 zeigt, dass Größenunterschiede zwischen den Gruppen (gemessen an Mitarbeiteranzahl und Bilanzsumme) wesentlich und statistisch signifikant sind. Unternehmen, deren Ergebnisprognosen extrem überschätzt oder extrem unterschätzt wurden, sind im Durchschnitt kleiner. So weisen beide extremen Gruppen auch nur annäherungsweise die Hälfte der Marktkapitalisierung der Vergleichsgruppenunternehmen auf. Ebenso grenzt sich die Kapitalstruktur der Gruppen voneinander ab. Da Finanzinstitute und Versicherungen aus dem Datensatz ausgeschlossen sind, werden hierfür Net Operating Assets (NOA)[31,32] und Net Financial Expenses (NFE)[33] gegenübergestellt. Auffällig ist die ungleiche Relation zwischen NOA und NFE unter den Gruppen. Insbesondere extrem überschätzte Unternehmen weisen hohe Finanzierungskosten in Relation zu operativen Vermögenswerten auf. Im Gegensatz dazu sind unterschätzte Firmen sehr niedrigen Finanzierungskosten ausgesetzt. Dies spiegelt auch die Hebelwirkung der Kapitalstruktur (Leverage) wider, wonach überschätzte (unterschätzte) Firmen einen höheren (geringeren) Verschuldungsgrad als die Vergleichsgruppe ausweisen. Zinsaufwendungen scheinen unter anderem auch den Jahresgewinn zu beeinflussen, da der Gewinn-pro-Aktie bei extrem überschätzten Unternehmen im Gegensatz zu den beiden anderen Gruppen negativ ausfällt. Zusätzlich scheinen extreme Überschätzer auch im operativen Geschäft schlechtere Ergebnisse auszuweisen. Der operative Cash Flow ist signifikant geringer gegenüber den Vergleichsunternehmen. Demgegenüber können unterschätzte Firmen einen deutlich höheren operativen Cash Flow aus ihren Geschäftstätigkeiten erzielen. Die Betrachtung der Kapitalflussrechnung in Verbindung mit Forschungs- und Entwicklungskosten (F&E) verdeutlicht die höheren Aufwendungen für den Ausbau künftiger Geschäftsfelder (relativ zu Total Assets) in den extremen Gruppen. Hohe F&E-Kosten bei gleichzeitig niedrigem operativen Cash Flow können als Indiz gesehen werden, dass ein Unternehmen gerade neue Geschäftsfelder erschließen will, aber aus diesen noch wenig Umsatz generiert. Dies spricht für kostenintensive Wachstumsinvestitionen, die insbesondere bei überschätzten Prognosen den Jahreserfolg belasten. Analysten scheinen folglich gerade expandierende Unternehmen falsch einzuschätzen, indem sie zu schnell eine hohe Profitabilität neuer Projekte erwarten und zugleich die verbundenen Aufwendungen vernachlässigen (Überschätzer). Dies wird auch bei der Verteilung der extremen Prognosefehler auf die

[31] NOA umfasst das betriebsnotwendige Vermögen ohne Finanzanlagen. Es wird vereinfachend angenommen, dass Finanzanlagen für Nicht-Finanzinstitute die operativen Tätigkeiten nur unterstützen und damit einen neutralen Nettobarwert aufweisen. Damit ist nur NOA für die Unternehmensbewertung relevant; vgl. z.B. Feltham und Ohlson (1995), S. 689-731.
[32] Vgl. für die Berechnung z.B. Callen und Segal (2005), S. 412 f.
[33] Vgl. für die Berechnung z.B. z.B. Callen und Segal (2005), S. 412 f.

unterschiedlichen Industriefelder ersichtlich. Hierzu präsentiert Tabelle 3 die absolute und relative Höhe der Fehlergruppen unterteilt nach Industriefeldern. Gerade sich schnell transformierende Technologiesektoren weisen höhere extreme Prognosefehler auf. Probleme eines volatilen Marktumfelds werden nicht nur bei Betrachtung der unterschiedlichen Industrien ersichtlich, sondern auch über den zeitlichen Verlauf der Prognosefehler aller Branchen. Gerade zu Höhepunkten weitreichender Marktkrisen werden Prognosen signifikant schlechter, was auch die Anzahl an extremen Überschätzern erhöht.[34] Gleichzeitig sinkt die Zahl der Unterschätzer.

Zuletzt ist auch die Anzahl der Analysten selbst entscheidend, die Prognosen für ein Unternehmen abgeben. So sinkt die Wahrscheinlichkeit eines extremen Prognosefehlers mit steigendem Interesse von Analysten.

Tabelle 2: Ausgewählte Bilanzkennzahlen der Untersuchungsgruppen

	Mittelwerte			t-Test / U-Test (p)		
Ausgesuchte Unternehmenskennzahlen	(A) Extreme Überschätzer	(B) Prognosefehler Vergleichsgruppe	(C) Extreme Unterschätzer	(B)*(A)	(B)*(C)	(A)*(C)
Mitarbeiter††	6,89	14,18	9,30	***	***	**
Total Assets†	6.929,66	23.834,76	10.714,64	***	***	***
Net Operating Assets†	3.994,81	11.067,07	4.191,80	***	***	*
Net Financial Expenses†	113,41	204,68	6,26	***	*	*
Leverage	0,34	0,29	0,22	***	***	***
EPS	-1,66	6,13	6,99	***	**	***
Operativer Cash Flow†	162,56	1.875,48	540,98	***	***	***
Issued Capital†	1.602,44	3.456,75	1.461,76	***	***	
R&D Expenditures†	136,90	246,13	114,28	***	***	
Analysten pro Unternehmen	4,70	7,33	4,78	***	***	

† in Mio.
†† in Tsd.

* 10%
** 5%
*** 1%

[34] Z.b. Dot-Com-Blase, die im Jahr 2000 begann und über zwei Jahre den Kapitalmarkt belastete, oder die Finanzkrise, welche sich in den Jahren 2008 und 2009 besonders auf Ergebnisprognosen auswirkte.

Tabelle 3: Verteilung der Prognosefehler nach GICS-Industrieklassifizierung[35] von 2000-2012

Industrie	(A) Extreme Überschätzer		(B) Prognosefehler Vergleichsgruppe		(C) Extreme Unterschätzer	
Energy	137	(5,9%)	630	(3.8%)	146	(6.9%)
Materials	266	(11,4%)	1619	(9.9%)	247	(11.7%)
Industrials	566	(24,2%)	4139	(25.2%)	510	(24.1%)
Consumer Discretionary	502	(21,5%)	3487	(21.2%)	412	(19.5%)
Consumer Staples	90	(3,9%)	1407	(8.6%)	116	(5.5%)
Health Care	167	(7,1%)	1471	(9%)	187	(8.8%)
Information Technology	545	(23,3%)	2753	(16.8%)	385	(18.2%)
Telecommunication Services	25	(1,1%)	336	(2%)	57	(2.7%)
Utilities	39	(1,7%)	572	(3.5%)	56	(2.6%)
Total	2337	100%	16414	100%	2116	100%

Jahr	(A) Extreme Überschätzer		(B) Prognosefehler Vergleichsgruppe		(C) Extreme Unterschätzer	
2000	195	(8.3%)	1368	(7%)	176	(5.8%)
2001	297	(12.7%)	2084	(7.3%)	269	(4.4%)
2002	227	(9.7%)	1593	(6.5%)	205	(5.4%)
2003	160	(6.8%)	1123	(6.2%)	145	(7.6%)
2004	103	(4.4%)	723	(6.2%)	93	(13.4%)
2005	130	(5.6%)	912	(7.2%)	118	(9.5%)
2006	137	(5.9%)	961	(8.6%)	124	(8.2%)
2007	160	(6.9%)	1137	(9.6%)	147	(8.1%)
2008	263	(11.2%)	1846	(9%)	238	(4.7%)
2009	227	(9.7%)	1593	(8.6%)	205	(8.9%)
2010	149	(6.4%)	1046	(8.4%)	135	(13.8%)
2011	144	(6.2%)	1010	(7.9%)	130	(6.1%)
2012	145	(6.2%)	1018	(7.5%)	131	(4.1%)
Total	2337	100%	16414	100%	2116	100%

Zusammenfassend kann für die Auswertung allgemeiner Unternehmenscharakteristika festgehalten werden, dass extreme Prognosefehler vermehrt bei kleineren und schnell wachsenden Unternehmen auftreten. Solche Unternehmen sind vermehrt in Bereichen der Informationstechnik angesiedelt. Diese haben tendenziell volatilere Jahresgewinne, was in Konsequenz die Ergebnisprognosefehler erhöht. Um genauere Unterschiede zwischen den einzelnen Gruppen zu erhalten – insbesondere zwischen extremen Über- und Unterschätzern, die in einigen Bereichen allgemeiner Charakteristika ähnliche Merkmale aufweisen – wird nachfolgend die Profitabilität der Unternehmen analysiert.

3.4. Analyse der Profitabilität

Nachdem der vorangehende Abschnitt das Profil von Unternehmen mit extremen Prognosefehlern durch die Betrachtung der Vermögensstruktur und allgemeiner Charakteristika analysiert hat, soll im Folgenden nun speziell auf die Profitabilität eingegangen werden. Für diese Auswertung wird das DuPont-Bewertungs-Schema[36] herangezogen. Dieses verkettet algebraisch einzelne relevante Werttreiber nach einer fest strukturierten Vorgehensweise. Die Gesamtkapitalrentabilität (ROA[37]) wird in ihre jeweiligen Bestandteile zerlegt, wobei mit jeder weiteren Disaggregation der Werttreiber tiefere

[35] GICS steht für "Global Industry Classification Standard" und gruppiert Unternehmen nach ihren primären Umsätzen in Branchen. Die Rating Agentur Standard & Poors's veröffentlicht dieses Klassifizierungsschema.
[36] Das DuPont-Schema wurde ursprünglich im amerikanischen Konzern DuPont entwickelt und ist daher nach diesem benannt.
[37] Engl. Return on Assets (ROA).

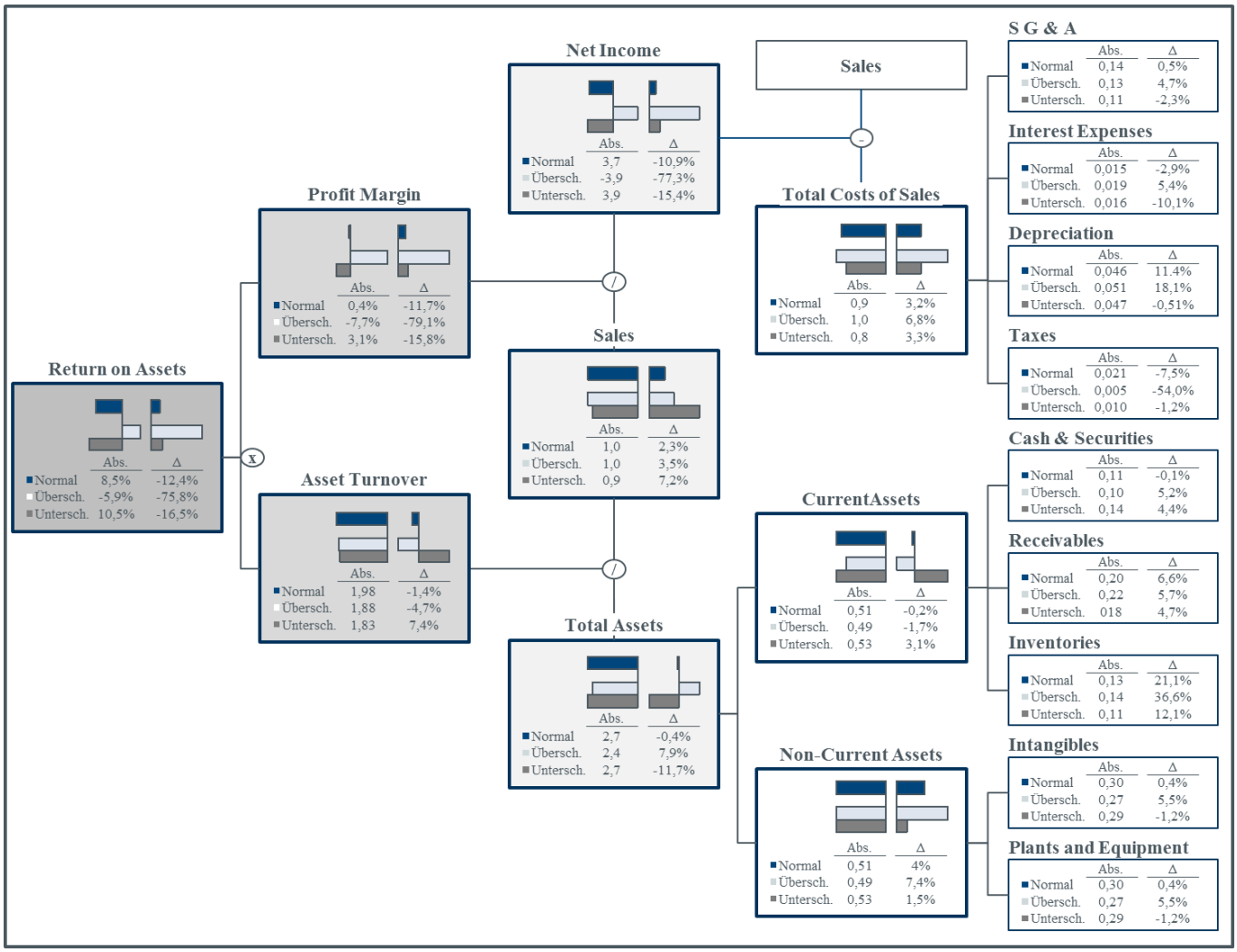
Einblicke in den Wertschöpfungsprozess eines Betriebes gegeben werden. Dieses Schema wird häufig von der einschlägigen Literatur[38] aus dem Bereich der externen bilanzorientierten Unternehmensbewertung für die Profitabilitätsermittlung vorgeschlagen. Darüber hinaus ist auch dessen Nutzen im Bereich der Ergebnisprognoserechnung erfolgreich empirisch belegt worden.[39]

Die Gegenüberstellung der wichtigsten Bestandteile der DuPont-Analyse soll Aufschluss geben, ob und inwieweit sich Werttreiber der Profitabilität von Unternehmen mit extremen Prognosefehlern von der Vergleichsgruppe unterscheiden. Dafür werden jeweils der absolute Wert eines Treibers sowie dessen Veränderung zum Vorjahreswert zum Zeitpunkt der Fehleinschätzung analysiert.

Abbildung 5 stellt die DuPont-Profitabilitätsanalyse von Unternehmen mit extremen Prognosefehlern (Über- bzw. Unterschätzer) der Vergleichsgruppe, also Firmen mit durchschnittlichen Prognosefehlern, gegenüber. Dabei wird für jede Komponente sowohl der absolute Wert für das korrespondierende Jahr des Prognosefehlers angegeben, als auch seine prozentuale Veränderung zum Vorjahr. Bereits die Ausgangskennzahl der DuPont-Analyse, Return on Assets, weist zwischen den Gruppen signifikante Unterschiede auf (Signifikanzniveau i.H.v. 1%). Während die Vergleichsgruppe im Durchschnitt eine Rentabilität von ca. 8,5% aufweist, erzielen unterschätzte Firmen im gleichen Zeitraum sogar 10,5% Rendite. Hingegen verzeichnen überschätzte Firmen einen extremen Profitabilitätsrückgang (ca. -75,8%) im Vergleich zum Vorjahr und erwirtschaften in Konsequenz eine negative Gesamtkapitalrentabilität von ca. -5,9%.

[38] Vgl. u.a. Penman (2012), S. 371-379; Lundholm und Sloan (2006), 92-99.
[39] Vgl. z.B. Fairfield und Yohn (2001), S. 371-385; Nissim und Penman (2001), S. 109-154; Amir et al. (2011), S. 302-327.

Abbildung 5: Untersuchung der Profitabilität nach der DuPont-Werttreiberanalyse[40]



Die nächste Ebene unterteilt Profitabilität in Profitmarge und Kapitalumschlag (Asset Turnover). Asset Turnover misst, wieviel Umsatz durch das eingesetzte Kapital generiert wird, wohingegen Profit Margin ein Indiz dafür ist, wie effektiv das Kostenmanagement während der Umsatzgenerierung ist. Im Einklang mit bisherigen Erkenntnissen[41] liefert der absolute Wert des Kapitalumschlages auch für die Erklärung extremer Ergebnisprognosefehler keine eindeutigen Hinweise. Allerdings zeigt seine Veränderung, dass unterschätzte (überschätzte) Firmen eine deutliche Verbesserung (Verschlechterung)

[40] Für jede Kennzahl ist sowohl der absolute Wert im Jahr des extremen Ergebnisprognosefehlers angeben, als auch die prozentuale Veränderung (Δ) im Vergleich zum Vorjahr. Balkendiagramme visualisieren zusätzlich die absoluten bzw. prozentualen Veränderungen. Alle Kennzahlen außer ROA, ATO, PM sind durch Total Assets normiert. Total Assets wurden mit Total Equity skaliert.

[41] Studien konnten belegen, dass die Profitmarge den unterschiedlichen Erfolg von Unternehmen erklären kann. Jedoch besitzt die reine Betrachtung des Kapitalumschlags wenig Aussagekraft. Vgl. z.B. Fairfield und Yohn (2001), S. 371-385.

zum Vorjahr aufweisen. Bei weiterer Disaggregation ist zu erkennen, dass von Analysten unterschätzte Unternehmen eine deutliche Umsatzsteigerung (7,2%) bei moderatem Ausbau der verwendeten Kapazitäten[42] verzeichnen können. Im Gegensatz dazu bauen extrem überschätze Unternehmen ihre Infrastruktur aus[43], ohne dabei absolut gesehen mehr Umsatz als die beiden anderen Gruppen zu generieren.

Die Analyse der Profit Margin legt klare Gruppenunterschiede offen. Extrem überschätzte Unternehmen verzeichnen im Jahr der Fehlprognose überwiegend negative Gewinnmargen durch einbrechende Jahresgewinne. Dies ist primär durch steigende Aufwendungen und Abschreibungen zu erklären. Hingegen erwirtschaftet die Gruppe der unterschätzten Firmen persistente, überdurchschnittlich hohe Gewinne bei gleichzeitiger Reduktion involvierter Aufwendungen.

Die empirischen Ergebnisse deuten darauf hin, dass extreme Schätzfehler insbesondere durch Veränderungen der internen Geschäftsprozesse entstehen. Investitionen und Wachstum können kurzzeitig das Jahresergebnis mindern. Analysten scheinen diese steigende Kostenstruktur bei ihren Prognosen ungenügend zu berücksichtigen. Hieraus resultieren steigende Ergebnisprognosefehler. Dies wird durch die Homogenität der Umsatzzahlen zwischen den Firmen bestätigt. Extreme Überschätzer weisen überdurchschnittliches Umsatzwachstum gegenüber der Vergleichsgruppe aus. Folglich scheinen rückläufige Verkaufszahlen nicht extreme Schätzfehler erklären zu können. Die Gesamtmarktentwicklung, die Verkaufszahlen stark beeinträchtigt, erscheint auch aufgrund der Verfügbarkeit von Informationen transparenter als die Entwicklung eines einzelnen Unternehmens. Folglich sind einbrechende Jahresgewinne, die aus unternehmensinternen Prozessen resultieren, als primäre Treiber extremer Ergebnisprognosefehler anzunehmen.

[42] Der Anstieg von kurz- und langfristigen Anlagen ist dabei nur unterproportional im Vergleich zur Umsatzsteigerung. Darüber hinaus zeigt diese unternehmerische Gesamtbetrachtung eher einen Rückgang der eingesetzten Ressourcen (Plants and Equipment, Intangibles), was für eine effektive Produktion spricht.
[43] Siehe z.B. jeweils 5,5 Wachstumsinvestitionen im Bereich Plants and Equipment sowie Intangible Assets.

4. Analyse der Beständigkeit extremer Ergebnisprognosefehler in Folgejahren

4.1. Zeitlicher Verlauf extremer Ergebnisprognosefehler

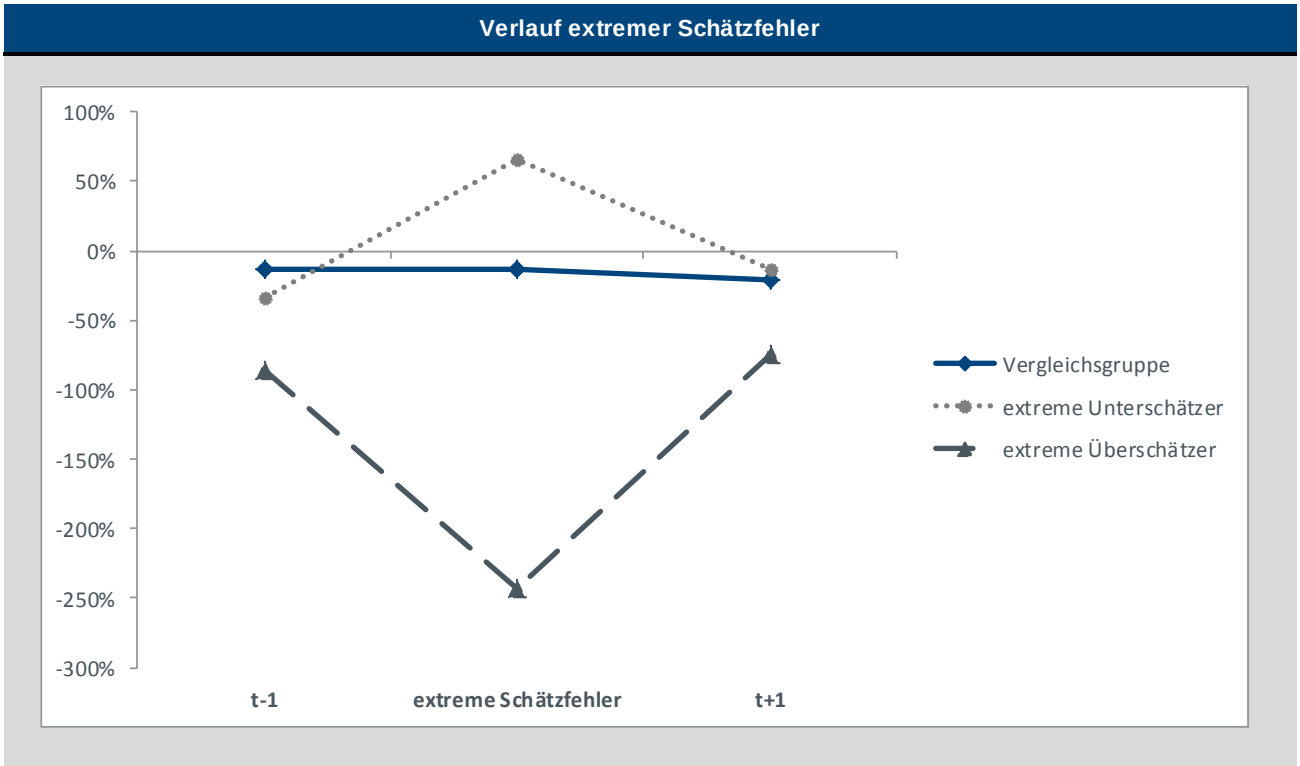
Bisher wurden extreme Ergebnisprognosefehler als rein singuläres Ereignis betrachtet. In diesem Abschnitt soll nunmehr untersucht werden, wie es sich um die Genauigkeit von Ergebnisprognosen vor bzw. nach dem Jahr des extremen Schätzfehlers verhält. M.a.W. wird der Frage nachgegangen, ob fehleingeschätzte Unternehmen bereits vor dem extremen Ergebnisprognosefehler auffällig abweichende Schätzfehler aufweisen, sowie ob diese Ergebnisprognosefehler im Folgejahr wieder sinken. Folglich wird untersucht, ob Analysten bereits vor der extremen Fehlprognose Schwierigkeiten hatten, ein Unternehmen einzuschätzen und ob im Folgejahr eine Korrektur dieser Fehlprognose stattfindet.

Für diese Fragestellung werden jeweils die Ergebnisprognosefehler der drei Gruppen (extreme Über- und Unterschätzer, Vergleichsgruppe) im Jahr vor, während und nach der extremen Fehleinschätzung gemessen. Dabei wird für jede Gruppe der Gesamtdurchschnittswert angegeben. In Abbildung 6 ist zu erkennen, dass der Ergebnisprognosefehler der Vergleichsgruppe zeitlich stabil bleibt.

Der durchschnittliche absolute Prognosefehler liegt zu den drei Betrachtungszeitpunkten bei ca. -18% (Überschätzung). Demgegenüber unterscheidet sich das Profil des zeitlichen Verlaufs extremer Unterschätzer deutlich. Im Vorjahr der Unterschätzung liegt der Fehler von Analysten sogar unterhalb der Vergleichsgruppe bei ungefähr -33%. Damit werden Unternehmen im Jahr vor einer extremen Unterschätzung tendenziell überschätzt. Jedoch dreht dieser im Jahr der extremen Fehlprognose von einer Überschätzung zu einer extremen Unterschätzung mit ca. 66% Prognoseabweichung. Analysten haben folglich die Entwicklung des Unternehmens deutlich unterschätzt. Der hohe Ergebnisprognosefehler spiegelt die Überraschung des Jahresergebnisses wider. Allerdings ist dieser Überraschungseffekt transitorisch. Bereits im Folgejahr ist der Grund der Unterschätzung entweder auf Seiten des Unternehmens nicht mehr aufgetreten oder Analysten haben ihre Ergebnisprognosen adäquat angepasst. In Folge hebt sich im Jahr nach der extremen Unterschätzung der Ergebnisprognosefehler nicht mehr von der Vergleichsgruppe ab. Der Fehler weist eine Mittelwertrückkehr auf (sog. Mean-Reversion-Effekt).[44]

[44] Die Mittelwertrückkehr beschreibt die Theorie, dass einige kapitalmarktbasierte Kennzahlen eine Regression zu einem Mittelwert vergleichbarer Unternehmen aufweisen. Nissim und Penman (2001), S. 109-154 untersuchen und belegen eine Mittelwertrückkehr für Komponenten der DuPont-Analyse.

Abbildung 6: Zeitlicher Verlauf extremer Ergebnisprognosefehler45



Unternehmen, deren Ergebnisse extrem überschätzt werden, besitzen hingegen andere Charakteristika. Sie unterscheiden sich stark von den beiden anderen Gruppen. Bereits im Jahr vor der extremen Fehlprognose ist diese Gruppe mit rund -86% überschätzt. Analysten scheinen Schwierigkeiten zu haben, diese Unternehmensgruppe zu bewerten. Die Schwierigkeiten scheinen sich im Jahr der extremen Fehlprognose zu verstärken. Hier ist eine Ergebnisabweichung von ca. -250% zu beobachten. Auch in dieser Gruppe greift der Mean-Reversion-Effekt. Jedoch kehrt der Fehler nicht auf das Niveau der Vergleichsgruppe zurück, sondern nur auf den Vorjahreswert des extremen Fehlers. Der Abstand zu den Vergleichsgruppen ist mit einer Fehlerdifferenz von über 50% erheblich. Folglich passen Analysten ihre Ergebnisprognosemodelle an die Unternehmensspezifika nicht adäquat an.

[45] Dabei beschreibt t-1 das Jahr vor dem extremen Prognosefehler und t+1 das Folgejahr.

4.2. Veränderung bilanzieller Kennzahlen vor und nach extremen Prognosefehlern

Um abschließend die unterschiedliche Beständigkeit der extremen Prognosefehler zu erklären, werden bilanzielle Kennzahlen um den zeitlichen Verlauf der Ergebnisprognosefehler analysiert. Hierfür werden insbesondere Profitabilitätskennzahlen des bereits vorgestellten DuPont-Schemas gegenübergestellt (siehe Tabelle 4).

Bereits die oberste Kennzahl dieses pyramidal aufgebauten Bewertungsschemas – Return on Assets – zeigt erhebliche Unterscheide zwischen den Gruppen auf. Deutlich zu erkennen ist der große Anstieg des Return on Assets vom Vorjahr zum aktuellen Geschäftsjahr des extremen Ergebnisprognosefehlers in der Gruppe der extrem unterschätzen Unternehmen. Im Jahr der extremen Fehlprognose steigt der Return on Assets um knapp 10%. Diese positive Entwicklung wurde von Analysten scheinbar nicht erwartet und kann folglich auch die extreme Fehlprognose des Ergebnisses erklären. Im Folgejahr bleibt die Profitabilität beständig. Indes erscheinen die Analysten nun sensibilisiert gegenüber der gestiegenen Rentabilität. Die Schätzabweichung kehrt damit zurück zur Vergleichsgruppe. Hingegen bricht die bereits im Vorjahr geringe Gesamtkapitalrentabilität in der Gruppe der überschätzten Unternehmen zum Zeitpunkt der extremen Fehlprognose des Ergebnisses massiv ein. Der Ergebnisprognosefehler steigt in dieser Gruppe auf durchschnittlich -250%. Obwohl sich die Unternehmensprofitabilität im Folgejahr verbessert, besteht weiterhin eine große Lücke zu der Vergleichsgruppe sowie zu der Gruppe der extremen Unterschätzer. Infolgedessen kehrt der Überschätzer wieder auf das Vorjahresniveau zurück.

Tabelle 4: Gegenüberstellung von Profitabilitätskennzahlen vor, während und nach dem Geschäftsjahr eines extremen Ergebnisprognosefehlers

		Jahr vor ext. Fehler	*Jahr des ext. Fehlers*	Jahr nach ext. Fehler
Return on Assets	*extreme Überschätzer*	5.5%	-4.0%	-0.6%
	Vergleichsgruppe	15.7%	14.9%	13.5%
	extreme Unterschätzer	3.7%	13.6%	13.1%
Profit Margin	*extreme Überschätzer*	2.5%	-3.1%	-1.2%
	Vergleichsgruppe	7.9%	7.9%	7.5%
	extreme Unterschätzer	-1.5%	6.5%	6.7%
Asset Turnover	*extreme Überschätzer*	1.91	1.77	1.86
	Vergleichsgruppe	1.92	1.88	1.84
	extreme Unterschätzer	1.77	1.89	1.91
Sales	*extreme Überschätzer*	0.97	0.94	0.96
	Vergleichsgruppe	0.96	0.95	0.94
	extreme Unterschätzer	0.88	0.90	0.90
Net Income	*extreme Überschätzer*	0.02	-0.02	-0.01
	Vergleichsgruppe	0.08	0.07	0.07
	extreme Unterschätzer	0.01	0.06	0.06

Ähnlich verhalten sich die Kennzahlen für die Gewinnmarge und den Jahresüberschuss. Im Gegensatz dazu sind Kapitalumschlag und Umsatzerlöse über den zeitlichen Verlauf der Schätzfehler relativ stabil. Dies bestätigt die bisherigen Ergebnisse der DuPont-Analyse, wonach vor allem das Verhältnis aus Aufwendungen und Erträgen (Zweig Profit Margin) eine maßgebliche Rolle für die Veränderung der Unternehmensprofitabilität spielt. Die Analyse grundlegender bilanzieller Kennzahlen lässt also einen klaren Zusammenhang zwischen extremen Ergebnisprognosefehlern und periodenbezogener Unternehmensprofitabilität erkennen. Danach scheinen Analysten sich bei der Erstellung ihrer Ergebnisprognosen stark an Vorjahreswerten zu orientieren. Bei starker Veränderung der vorjährigen Durchschnittswerte entstehen somit tendenziell extreme Ergebnisprognosefehler. Gegenüber unterschätzten Unternehmen scheinen Analysten adäquate Anpassungen ihrer Schätzmodelle zu treffen, wodurch im Jahr nach einer extremen Fehleinschätzung der Ergebnisprognosefehler „mean-reverting“ ist. Im Gegensatz dazu schaffen es Analysten

indes nicht, extreme Überschätzungen im Folgejahr ausreichend zu korrigieren. Obwohl sich der Ergebnisprognosefehler mindert, liegt dieser im Folgejahr einer extremen Fehlschätzung immer deutlich über dem Gesamtniveau der Vergleichsgruppe.

5. Zusammenfassung

Historische Ergebnisprognosen von Analysten dokumentieren große Unterschiede bezüglich ihrer Schätzgenauigkeit. Der absolute Ergebnisprognosefehler für europäische Unternehmen unterliegt korrelierend zu volatilen Marktsituationen einer Spanne zwischen 40% - 80%. Extreme Ergebnisprognosefehler von über 250% sind keine Seltenheit. Dabei fallen extreme Überschätzungen des Unternehmensgewinnes deutlich höher aus als Unterschätzungen. Zudem kommen Überschätzungen häufiger vor als Unterschätzungen. Dies stimmt mit bisherigen Erkenntnissen überein, dass Analysten zu Optimismus neigen. Eine bilanzkennzahlenorientierte Analyse von Unternehmen mit extremen Ergebnisprognosefehlern zeigt, dass diese Unternehmen spezielle Charakteristika aufweisen. So stehen hinter extrem überschätzten Ergebnisprognosefehlern vorwiegend kleinere Unternehmen mit höherem Verschuldungsgrad. Hohe Ausgaben im Bereich Forschung und Entwicklung bei niedrigem operativem Cash Flow sprechen dafür, dass sich überschätzte Unternehmen in einer Wachstumsphase befinden. Dafür spricht auch die Industrieklassifizierung, wonach extreme Prognosefehler häufiger in schnell wandelnden Branchen auftreten (z.B. IuK-Märkte). Eine Profitabilitätsanalyse zeigt darüber hinaus, dass ein hoher Ergebnisprognosefehler auch durch einbrechende Kapitalrendite entsteht. Im Gegensatz dazu weisen unterschätzte Unternehmen eine hohe Steigerung der Rentabilität sowie eine solide Kapitalstruktur auf. Die Auswertung der Beständigkeit der Ergebnisprognosefehler zeigt zudem, dass eine Unterschätzung im Folgejahr von Analysten i.d.R. korrigiert wird. Indes bleiben extreme Überschätzungen der Ergebnisprognose auch in Folgejahren bestehen.

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EHRENWÖRTLICHE ERKLÄRUNG

Ich versichere: Ich habe die Dissertation selbständig verfasst.

Andere als die angegebenen Hilfsmittel und Quellen habe ich nicht benutzt.

Die Arbeit hat keiner anderen Prüfungsbehörde vorgelegen.

Berlin, den 20.07.2015 Unterschrift