Kumulative Dissertation zum Themengebiet:

Essays on the valuation and reporting of intangible assets

Der Fakultät für Wirtschaftswissenschaften
der Universität Paderborn
zur Erlangung des akademischen Grades
Doktor der Wirtschaftswissenschaften
– Doctor rerum politicarum –

Vorgelegt von
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Content

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1. Acknowledgements

I learned over the years that pursing a PhD can be a long and sometimes lonely road, yet you do not undergo this journey without the help of a significant amount of people. Thus, I owe large gratitude to many great people. I, particularly, want to acknowledge the impact they had on the writing of this dissertation and my personal development of the last couple of years.

First, I want to say thank you to my dissertation committee. Special thank you to my supervisor, boss, and “sparring partner” for research ideas, Mr. Sönke Sievers (a.k.a. “Advocatus Diaboli”, self-proclaimed of course). Thank you for providing me with the opportunity to pursue a PhD and your continuous support throughout these years, especially in the last year. You have provided help in every step of my PhD, even when it was a late Friday evening or a Saturday morning. I have learned so much through our daily meetings about doing research. Thank you also for sending me to all these conferences and workshops without hesitance. They broadened my academic and personal horizon, even when your chair budget was driven deep into negative numbers (Mr. Sievers has always complained to colleagues that he is broke because of my constant travelling). Thank you to Urska Kosi for taking over the co-supervisor role and your support, especially in the last months of the job market. Thank you to Mr. Stephan Betz for your continuous support over the last years and agreeing to be on my committee (and for providing me with sweets whenever I had long coding or reading sessions at night). Lastly, thank you to Philip Yang for taking over the last spot in my committee.

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Next, I would like to take the time to thank deeply my co-authors that have worked with me on several papers over the last couple of years: Olga Ihl-Deviv’e, Gopal Krishnan, Wayne Landsman, Ulf Mohrmann, Boaz Noiman, Jan Riepe, Sönke Sievers, and Pia Stoczek. I feel beyond blessed that you gave me the opportunity to work with you. I have learned so much while working with you. Even I know that sometimes I cannot be great co-author (especially when I complain about tests, writing, coding etc.) but I am very thankful that you have always kept up with my bitterness. I look forward to how our projects will evolve. From this group of great people, I would like to thank two people especially. First, my gratitude goes out to my roomie and friend at the University of North Carolina: Boaz Noiman. At North Carolina, we quickly understood that we have common interests in many topics. Your critical thinking about research is something that I deeply admire and I learned so much through our regular interactions. Moreover, I have always enjoyed our common research time. More importantly, you have also become a great friend outside of academia. Second, special thanks to Jan Riepe. I am really happy that you have joined Paderborn during Covid and I got to know you. You have become a true academic companion that I have looked up to from the beginning. I have always cherished our productive meetings in Tübingen and our after-work beers. It seems to me that Tübingen has become my third “academic home”.

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I also want to thank the entire TAF department for the continuous support throughout my PhD studies. Thank you to all the professors and my entire fellow (past) PhD colleagues in the department. Special thanks to my lunch buddies Mathis Heidmann, Pascal Schulz, and Daniel Plückebaum. Together with Mr. Betz, you constantly provided me with lunch "asylum" in my last year when I was alone on Q2. I always enjoyed our lunch discussions over football and the coffee time after.

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I also want to thank my family that have guided and supported me over the last years without hesitance. To my mom, Monika Liß, for her constant support throughout my life. Your care and work ethics is something that I deeply admire. To my aunt, Helga Verhof, who has been supportive in my academic career in accounting and finance from the “get go” and our common interest in debit and credit. I also want to thank two special people who had a significant impact on my personal development, yet, passed away during my PhD studies. First, my father, Paul Dieter Liß, and second my uncle Karl Heinz Verhof. Without those two, I would not have been here. If I become half of the person you were, I would be a happy man. Thus, I dedicate this dissertation to them. I also want to thank my second family, my American family: Deborah Bobbitt, Ollie Bobbitt, my brother Perry Andrew Bobbitt, Jessica Bobbitt, Ashby

Bobbitt, Tammy & Dennis Anderson, and Robin Davenport. I am thankful that you have stepped into my life and you have taken a chance on me. You showed me a path for my life, when I was a “lost” 17-year-old kid from Germany.

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Lastly, I want to take the time to quote one of the great philosophers of my time, Snoop Dog:

"*Last but not least... I want to thank me. I want to thank me for believing in me, I want to thank me for doing all this hard work. I wanna thank me for having no days off. I wanna thank me for never quitting*."

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Synopsis to the cumulative dissertation

"Essays on the valuation and reporting of intangible assets"

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1. Introduction

Innovation and its underlying assets, i.e., intangible assets[1], are a central driver of economic growth (e.g., Solow 1957; Romer 1990; Corrado et al. 2009). Financial accounting standard setters define intangible assets (or intangibles) as non-financial assets that lack physical substance (ASC 350, IAS 38). Common examples of intangible assets are patents, customer lists, licenses, trademarks and -names, and franchises. With regard to their reporting, standard setters distinguish between internally generated and externally bought intangible assets. While many internally generated intangibles such as research and development (R&D) and advertising expenditures are expensed when incurred, acquired intangible assets from individual transactions or business combinations are capitalized on the statement of financial position and amortized or tested for impairment over time. The different accounting treatment of intangible assets creates reporting effects, which affects investor's decision-making. The Financial Accounting Standards Board (FASB) and the International Accounting Standards Board (IASB) acknowledge potential shortcomings in the reporting of intangible assets and have, thus, issued multiple project calls for improving intangible asset reporting and disclosure. The goal of this dissertation is to contribute to the debate by providing essays on the valuation and reporting of intangible assets.

This synopsis constitutes the dissertation's preface and is structured as follows. The next section outlines the dissertation's overall content and structure (section 2). Thereafter, in section 3, I formulate the dissertation's research questions, summarize the key findings, and demonstrate its contribution to the literature. Section 4 highlights paths for future research based on this dissertation's insights. Finally, section 5 informs regarding the publication status of the dissertation's papers and provides each paper's title page for one's initial reading.

[1] Throughout this dissertation, I use the terms "intangible assets" and "intangibles" interchangeably.

2. Content and contributions

My dissertation centers around the role of intangible assets in firm's financial accounting and reporting environment and how firms report different intangible assets to stakeholders, such as investors, competitors, and regulators. The dissertation is cumulative and comprises three academic papers with equal contribution to the complete works. This includes questions related to the measurement and reporting of intangible assets in firms' financial reports and other information sources such as website of the US Patent and Trademark Office (USPTO) and how the accounting treatment of intangible asset shapes both firms' and investor's decision making. Intangible assets can either be generated internally through human capital investment or be externally bought through business combination or singular transactions. Previous literature in financial accounting, finance, and economics has largely focused on measuring and the reporting of internally generated intangible assets. In particular, common proxies for the amount internally generated intangible assets have been R&D expenditures (e.g. Lev and Sougiannis 1996), advertising expenditures (Kallapur and Kwan 2004), and the amount of patents being granted (e.g. Hall et al. 2005; Kogan et al. 2017). Acquired intangible assets, on the other hand, remain largely unexplored due to data reasons. In order to provide a contribution to the literature, I build for this dissertation a hand-collected database on acquired intangible asset net amounts for over 2000 US-firms (about 20,000 firm-year observations) to answer fundamental questions with regard to the equity pricing and auditing of acquired intangible assets. Paper A and B provide contributions to the research stream of acquired intangible assets. In contrast, Paper C focuses on the reporting of one important internally generated intangible asset, patents.[2] In particular, I investigate how patent enforcement and litigation affect the patent disclosure decision of firms. Given the rising numbers of IP litigation (Bessen et al. 2018; Mezzanotti 2021) studying the effects of IP litigation on the information environments of firms is crucial.

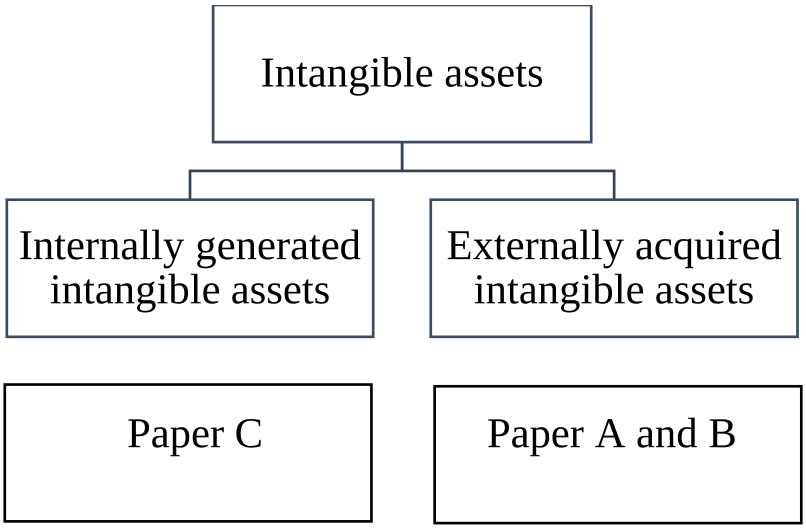
[2] Patents can also be bought through business combinations or singular transactions. However, given that my research design focuses on patent pre-grant disclosures, I only focus here on internally generated patents.

This is especially important given that shielding innovative activities from IP litigation has become a major determinant for the success of firms.

Taken together, Figure 1 depicts the two different forms of intangible asset acquisition and the structure of this dissertation in a diagram.

Figure 1: Intangible assets and structure of dissertation

Notes: This figure depicts the different acquirement of intangible assets and the structure of this dissertation. In fact, paper A and B focus on externally acquired intangible assets from the perspective on equity pricing and auditing. Paper C focuses on internally generated intangibles and the effects of IP litigation on the disclosure decision of one internally generated intangible asset, patents.



3. Research questions, findings, and contributions

3.1 Paper A: The pricing of acquired intangibles

In **paper A (Landsman, Liss, Sievers 2022)** of my dissertation, we examine the value relevance of acquired intangible assets in equity valuation. In particular, we investigate value relevance of different specifications of acquired intangible assets on stock prices using a new hand collected database on intangible asset amounts that allows us to disaggregate acquired intangible assets into different classes (tech, customer, contract, marketing) and economic lifetimes (definite and indefinite). We base our analysis on an adjusted Ohlson (1999) valuation framework in line with Barth et al. (1999, 2005), which imposes a triangular valuation structure of abnormal earnings, accruals, and autoregressive processes of net values of intangibles on valuation coefficients. We predict and find that net amounts of acquired intangibles are positively priced in equity markets. First, we find that both definite and indefinite intangible assets are positively associated with stock prices demonstrating a high relevance for equity investors. Second, we investigate four different intangible asset classes: tech-, customer-, contract-, and marketing intangibles. Other categories such as customer-, contract-, and marketing intangibles are also value relevant, yet, not as economically relevant as tech intangibles. Third, we disaggregate our four intangible asset classes into definite and indefinite intangible assets and find positive associations for definite and indefinite intangibles. Fourth, our empirical findings speak against the recent FASB proposal for subsuming intangible assets, in particular customer intangibles and non-compete agreements, into goodwill. While this study finds no associations between non-compete agreements and stock prices, we find significantly positive coefficients for customer-related intangibles. These results imply that subsuming several intangible assets, as e.g., customer intangibles, into the goodwill would lead to a loss of relevant information for equity investors.

This paper contributes to the debate on capitalizing acquired intangible assets on the balance sheet. While the literature on the value relevance of internally generated intangible assets is vast, evidence on acquired intangible assets is scarce due to data availability reasons with two exceptions. Whereas King et al. (2023) and McInnis and Monsen (2023) investigate the profitability forecasting ability and value relevance of fair values of acquired intangibles in business combinations at the time of acquisition, we provide evidence on the value relevance of net amounts of acquired intangibles beyond the acquisition date using large firm-panel data that includes fair values of intangibles from business combinations and individual transactions that reflect amortization and potential impairments.

Overall, this study answers recent calls from both academics and standard setters (FASB and IASB) to investigate the usefulness of acquired intangible asset amounts. Moreover, this study is based on the most comprehensive dataset for acquired intangible asset classes tracking their post-acquisition values over time. Eventually, the paper directly speaks to potential losses in decision-relevant information for equity market participants when changing accounting for acquired intangible assets.

3.2 Paper B: Acquired intangible assets, CAM disclosures, and audit risk

Building on the prior results and the database from Landsman et al. (2022), **paper B (Liss, Riepe, Sievers 2023)** investigates the association between net values of acquired intangible asset classes, their inherent audit risk, and audit fees.

Using the hand-collected sample on the net amounts of acquired intangible assets from 2009 to 2021, we find that acquired intangibles are positively associated with audit fees; however, our results support our predictions that they are easier -and thus less costly- to audit than goodwill. This finding holds true for both definite and indefinite acquired intangibles. In line with our further predictions, definite intangible assets are less expensive to audit than indefinite intangible assets. Nevertheless, we find a large heterogeneity among the different classes of acquired intangibles regarding their association with audit fees. Definite tech (patents and developed technology) and indefinite marketing (trademarks and brands) intangibles are significantly positively associated with audit fees, while many other intangible asset classes remain non-significant. This evidence is consistent with higher risk for auditors but also with more effortful audits attributable to indefinite acquired intangibles and their annual impairment testing.

Next, and most importantly, we examine whether the issuance of intangible-CAMs moderates the relation between acquired intangible assets and audit fees. In a first descriptive analysis, we document that intangible-CAMs are longer than CAMs on other asset classes such as tangible assets or other complex accounting estimates such as taxes. A detailed content analysis shows that the auditor highlights the use of internal and external valuation specialists in around 52 percent of all intangible-CAMs. This is 2.5 times as often compared to the valuation of tangible assets with tangible CAMs (only about 19 percent) or tax-related CAMs (about 22 percent) and about the same compared to goodwill CAMs (about 52 percent) but slightly less in CAMs on the initial business combinations (about 54 percent). The result on the use of valuation experts and specialists not only highlight the auditor's use of additional validation and confirmation of their work by specialists. Results also reveal that the auditors actively communicate the employment in their audit report, potentially to signal their substantial audit work. We also see that, with an average of about 193 words, the description of how the auditor addressed intangible-related matters is longer than the description on most other topics such as taxes (175 words) or tangible assets (164 words), again pointing to the auditor's intentionally signaling their substantial work to the public in the audit report.

In a second analysis, our econometric results regarding the introduction of intangible-related CAMs show that the audit fee mark-up associated with acquired intangibles becomes lower after the public disclosure of intangible-related CAMs. Moreover, this result is explained by indefinite intangible assets. This finding is consistent with two interpretations: First, the initial mark-up on audit fees regarding the intangible assets might reflect additional procedures and time to audit these complex balance sheet items. Second, these results are also consistent with increasing the auditor's acceptable audit risk following from CAM disclosures.

This study contributes to two literature streams in the auditing space. First, we provide new evidence on the effects of complex estimates on audit fees. While several papers have provided evidence for the effects of financial assets (e.g., Cannon and Bedard (2018)), we provide evidence on the audit effects of different disaggregated intangible assets. Second, we contribute to the young and growing literature on CAMs, which shows partially conflicting results regarding the role of CAMs. In particular, while Klevak et al. (2023) provide evidence, that firms with more extensive CAM disclosures are associated with increased perceived uncertainty, Burke et al. (2023) highlight important impacts on CAM-driven disclosure effects, but acknowledge limited capital market effects. Within the paper, we contribute to this literature by showing that our results are consistent with results that auditors use CAMs to mitigate their audit risk.

This study also speaks to the recent calls from both academics and standard setters (FASB and IASB) by separately investigating the roles of the amounts of acquired intangibles and their costs as well as the benefits of capitalization apart from goodwill.

3.3 Paper C: IP disclosure under IP litigation

While paper A and B focus on acquired intangible assets, capitalized on firm's balance sheets, **paper C (Liss 2024)** investigates internally generated intangible assets and their disclosure decision. In particular, I investigate the patent disclosure decision of firms that are being litigated for their existing intellectual property. In particular, the protection of intellectual property (IP) is at the core of the innovation process and a necessity for the comparative advantage of firms and an entire economy. However, rising numbers of IP litigation cases have become a burden to firms with an estimated cost of 300 billion to the US economy (Bessen et al. 2018). Thus, firms consistently innovate new technologies under the uncertainty of being sued for their technology. More importantly, many firms have to decide whether to disclose innovations, which could expose them to new litigation. In this paper, I examine how IP litigation affects the disclosure of subsequent innovation.

Using data on patent pre-grant disclosures and patent litigation as the unit of observation with a design similar to Glaeser and Landsman (2021), I find that current IP litigation delays the disclosure of innovation (*delay effect*), while closed IP litigation accelerates the disclosure (*deterrence effect*). This evidence is consistent with firms delaying IP disclosures under IP uncertainty and accelerating IP disclosures when IP uncertainty is resolved. While the *delay effect* leads to lower knowledge spillover in form of lower patent citations, the *deterrence effect* mitigates incoming industry competition. Moreover, closed IP litigation also improves patent disclosure quality in form of longer and more readable patent descriptions. Difference-in differences estimations around the Supreme Court trial decision of eBay vs. MercExchange in 2006 provide additional evidence that when current IP litigation risks for computer & communication patents (lower injunction likelihood) are lowered, firms accelerate the timing of patent disclosures for this technology class in comparison to patents from other technological fields. These results are consistent with Mezzanotti (2021) that litigation costs affect patent disclosure decisions. Additionally, I investigate how different court enforcement influences the disclosure decision of litigated firms. Using the exposure of firms to the Court of Eastern Texas as a setting of weak IP enforcement[3], I find that plaintiff-friendly IP courts contribute to my observed disclosure effects. In particular, the disclosure effects for firms with an increased exposure to the Court of Eastern Texas are higher than for firms that are not as exposed.

My paper contributes to a long and vast literature on disclosure and litigation, which mostly focused on class action lawsuits and misbehavior of firms (see for example Bourveau et al. (2018) and Schantl and Wagenhofer (2023)). Here I contribute that asset specific litigation can also distort disclosure decisions, namely patent disclosures. Moreover, I contribute to the literature on the determinants of IP disclosures by providing evidence that IP litigation is a critical component of firm's IP disclosure policies.

This paper also contributes to the regulatory debate on potential externalities of rising IP litigation. Several academics in legal studies have raised negative concerns about the growing number of IP litigation. I document both negative and positive effects of IP litigation on the information environments of firms providing a new perspective to the debate of rising IP litigation and patent enforcement.

[3] For the literature on the differing effects of IP enforcement and "court shopping", see e.g. Moore (2001), Sohi (2003) or Jacobsmeyer (2018).

4. Future research

This dissertation offers various points of contact for future research, not only for accounting, but also for finance and innovation economics scholars. On the one hand, paper A and B offer opportunities for new research on acquired intangible assets as this asset class with its different classes (tech, customer, contract, marketing) and economic lifetimes (definite and indefinite) has not been fully explored due to data limitations. Given the uniqueness and the large magnitude of the hand collected acquired intangible asset database, this database offers many new angles for investigating the impact on acquired intangible assets on different firm effects such as debt contracting, intangible asset impairments, or even tax considerations. Given the recent calls of both FASB and IASB for more evidence-based research on intangible assets, this dissertation can spur new research on this angle. With regard to internally generated intangibles, paper C provides several opportunities for future investigations as well. In particular, the angle of patent litigation and the new insights gained on the effect of IP litigation on IP disclosures offer several research opportunities. In particular, researchers can investigate potential (firm) responses to patent litigation.

5. Publication status

This dissertation is cumulative and consists of three papers in the context of intangible assets. Each chapter corresponds to one paper. Please consider that the papers A, B, and C are continually revised for (re-)submission to leading academic journals. To date, early versions of Paper A and B are each already published within the SSRN working paper series. Please note that the dissertation's versions of Paper A, B, and C might not reflect the latest revisions in the future. Thus, potential references should be made to the up-to-date online versions.

The pricing of acquired intangibles

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ABSTRACT:
This paper investigates the value relevance of acquired intangible assets using a comprehensive sample for 1,647 publicly-listed US-firms from 2002 to 2018. This sample allows us to assign acquired intangible assets into different classes (e.g., tech-, customer-, contract-, and marketing-intangible assets) and their respective economic lifetimes (i.e., definite vs indefinite useful lives) to test their relevance for equity investors. We predict and find positive associations for most intangible assets, however with different economic significance. In particular, tech- and customer-related intangible assets are priced by equity investors. Furthermore, definite intangible assets are more relevant than indefinite intangibles. These and additional results aid firms and their equity investors' understanding of the economic impact of intangible assets, and also are potentially relevant to standard setters as they consider a proposal to subsume several intangible assets into goodwill.

Key words: Intangible assets, business combinations, equity pricing, valuation, standard setting

JEL Codes: G14, G32, M40, M41

Data availability: Data are available from the public sources cited in the text

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Acquired intangible assets, CAM disclosures, and audit risk

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ABSTRACT:
This paper investigates the association between net values of acquired intangible asset classes, their inherent audit risk, and audit fees. First, our findings using a large and hand-collected sample show that acquired intangibles, in general and especially with definite lifetimes, remain less expensive than the alternative accounting treatment: goodwill. Second, and most important, we show that auditors' use of intangible-related critical audit matters (CAMs) moderates this association in a difference-in-differences design. Intangible assets increase audit fees especially in high litigation industries, but intangible-related CAMs moderate the link between intangible assets and audit fees. These results are consistent with the hypotheses that public disclosure of intangible-related CAMs gives the auditor subject-specific protection against audit risks from acquired intangible assets. This, in turn, allows them to reduce audit fees. Overall, these results are important for auditors, standard setters and also inform researchers regarding the risk-reducing effects of CAM disclosures.

Key words: Intangible assets, auditing, business combinations, critical audit matters
JEL Codes: M40, M42, M48
Data availability: Data are available from the public sources cited in the text

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IP Disclosure under IP Litigation

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ABSTRACT:

Legal disputes over the ownership of intellectual property (IP) have tripled over the last three decades costing hundreds of billion US-dollars to the US economy. In this paper, I examine how IP litigation affects the disclosure of subsequent innovation. Using the timeliness of patent pre-grant disclosures, I find that current IP litigation delays the disclosure of innovation (*delay effect*). This evidence is consistent with firms delaying the disclosure of similar technologies until IP uncertainty is resolved. In contrast, firms accelerate innovation disclosures when they have closed IP case experience (*deterrence effect*). While the delay effect leads to lower knowledge spillover, the deterrence effect mitigates incoming industry competition. I confirm these findings using the Supreme Court decision of *eBay vs. MercExchange* within a difference-in-differences design, which lowered the potential costs of enforcement for defendants of computer patents. Patents even become more informative when firms have closed IP litigation. Finally, weak IP institutions such as more lenient courts contribute to those disclosure effects. Overall, this paper highlights both negative and positive externalities of IP litigation on IP disclosures.

Key words: voluntary disclosure, litigation, innovation, patents, regulation.
JEL Codes: D23, G38, O30, O31, O33, O34, O38
Data availability: Data are available from the public sources cited in the text.

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3. Studies of the dissertation

The pricing of acquired intangibles

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ABSTRACT:
This paper investigates the value relevance of acquired intangible assets using a comprehensive sample for 1,647 publicly-listed US-firms from 2002 to 2018. This sample allows us to assign acquired intangible assets into different classes (e.g., tech-, customer-, contract-, and marketing-intangible assets) and their respective economic lifetimes (i.e., definite vs indefinite useful lives) to test their relevance for equity investors. We predict and find positive associations for most intangible assets, however with different economic significance. In particular, tech- and customer-related intangible assets are priced by equity investors. Furthermore, definite intangible assets are more relevant than indefinite intangibles. These and additional results aid firms and their equity investors' understanding of the economic impact of intangible assets, and also are potentially relevant to standard setters as they consider a proposal to subsume several intangible assets into goodwill.

Key words: Intangible assets, business combinations, equity pricing, valuation, standard setting

JEL Codes: G14, G32, M40, M41

Data availability: Data are available from the public sources cited in the text

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The pricing of acquired intangibles

ABSTRACT:
This paper investigates the value relevance of acquired intangible assets using a comprehensive sample for 1,647 publicly-listed US-firms from 2002 to 2018. This sample allows us to assign acquired intangible assets into different classes (e.g., tech-, customer-, contract-, and marketing-intangible assets) and their respective economic lifetimes (i.e., definite vs indefinite useful lives) to test their relevance for equity investors. We predict and find positive associations for most intangible assets, however with different economic significance. In particular, tech- and customer-related intangible assets are priced by equity investors. Furthermore, definite intangible assets are more relevant than indefinite intangibles. These and additional results aid firms and their equity investors' understanding of the economic impact of intangible assets, and also are potentially relevant to standard setters as they consider a proposal to subsume several intangible assets into goodwill.

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1. Introduction

The accounting for intangible assets remains one of the most debated topics among accounting practitioners and academics. At the core of this debate is the extent to which recognized intangible assets provide relevant information that is also reliable to financial statement users, particularly investors. The purpose of this study is to investigate how net amounts of acquired intangible assets are reflected in security prices for 1,647 firms. In particular, we provide evidence of whether intangible assets are more or less value relevant depending on their nature (e.g., tech, customer, contract, and marketing) and economic lifetime (i.e., definite vs. indefinite).

Intangible assets are becoming an increasingly larger share of firms' assets, particularly those acquired during a business combination. This has led the Financial Accounting Standards Board (FASB) and International Accounting Standards Board (IASB) to reexamine standards on acquired intangible assets to assess whether acquired intangible asset amounts are verifiable (FASB 2019; IASB 2020). Although many internally generated intangibles such as research and development (R&D) and advertising expenditures are expensed, acquired intangible assets are capitalized in the statement of financial position.[1] Intangible assets can be acquired either through business combinations or individually by purchasing, e.g., patent rights or FCC licenses.

Statement of Financial Accounting Standards No. 141 (SFAS 141), *Business Combinations*, substantially changed the accounting for acquired intangibles, resulting in billions of dollars of intangible value being added to acquirers' statements of financial position. However, many critics contend that accounting amounts for acquired intangibles are unreliable for equity investors because intangibles are difficult to value and their valuation inputs often are unverifiable. As a result, reported intangible amounts are subject to managerial discretion

[1] Throughout we use the terms "intangible assets" and "intangibles" interchangeably.

that can result in a great deal of uncertainty regarding their true underlying value to the acquiring firm. Because of concerns that some acquired intangible amounts are difficult to verify, the Boards' deliberations include proposals to subsume certain individual intangible assets, such as customer related intangible assets and non-compete agreements, into goodwill.

In response to its current reexamination and its request for comment on its recent Exposure Draft, the FASB received over 100 comment letters from financial statement preparers, valuation and industry experts, and academics with different opinions on current standards and how best to improve them.[2] Although the comment letters reveal a wide variation in opinions regarding what changes, if any, are necessary to improve intangible asset accounting, there is little evidence to support whether accounting amounts of acquired intangibles are useful for equity investors. In addition, in recent years acquired intangible assets have become one third of the average merger and acquisition (M&A) deal value, adding billions to the statement of financial position of acquirers, and are a major determinant of merger success. Despite its importance for firms, investors, and standard setters, empirical evidence on this topic is limited, especially with regard to post transaction values of acquired intangibles. The purpose of this study is to fill the void by investigating if acquired intangible amounts are value relevant for equity investors and, if so, whether they have different pricing characteristics with regard to their nature and economic lifetime. Investigating the valuation implications of different approaches to accounting for acquired intangible assets can help inform the FASB as it assesses the merit of various positions under consideration.

Our sample comprises net amounts of acquired intangible assets from financial statements relating to 16,508 firm-year observations from 1,647 firms. Our sample period starts in 2002, the first year SFAS 141 was applied, and ends in 2018. We obtain *net amounts* of acquired

[2] The invitation to comment can be found following the link: https://www.fasb.org/jsp/FASB/Document_C/DocumentPage?cid=1176172950529&acceptedDisclaimer=true. Comment letters can be found following the link: https://www.fasb.org/jsp/FASB/CommentLetter_C/CommentLetterPage&cid=1218220137090&project_id=2019-720&page_number=1.

intangible assets disclosed in the notes section of annual financial statements, including information on acquired intangibles based on their economic lifetime (i.e., definite vs. indefinite) and their different classes as classified by US Generally Accepted Accounting Principles (US GAAP) (e.g., tech-, customer-, contract-, and marketing-intangibles). Our sample firms' market capitalization comprises at least 50% of the total market capitalization of US stock market's total capitalization in each year.

To address our research question, we follow prior value relevance research and employ a generalized system of the Ohlson (1999) model (Barth et al. 1999). This approach allows us to isolate the relation between acquired intangible assets and stock prices by applying a linear information dynamic structure that specifies each intangible asset coefficient as a function of each intangible asset's relation to abnormal earnings and its own time-series properties. This well-established research design requires a time-series of firm-level data and thus cannot be applied to assessments of value relevance of fair values of intangible assets based on purchase price allocations at date of acquisition (King et al. 2021; McInnis and Monsen 2021).

We estimate our system over the entire period, 2002 to 2018, and for the pre- (fiscal years 2002 - 2008) and the post SFAS 141 revision period (2009-2018) as a fully interacted model to test for differences in coefficients between the two periods. The subperiod analyses permit us to assess whether there is a change in value relevance of acquired intangible assets following the revision of SFAS 141 in 2007 (SFAS 141R), which increases disclosure requirements for impairment tests of goodwill and other indefinite intangibles and mandates the capitalization of in-process R&D. One of the main reasons for revising SFAS 141 was concern regarding the lack of guidance regarding assignment of intangible assets into particular classes, e.g., tech and customer, as well as the determination of their respective useful lives as definite or indefinite. Preparers were not satisfied with existing guidance on how to account for these assets and investors expressed concern that it was difficult to assess their valuation implications. The FASB partly addressed these concerns by providing additional guidance and requiring capitalization of acquired in-process R&D with the expectation that the revision would lead to an improvement in reporting quality (FASB 2014). By examining separately the pricing characteristics of acquired intangibles in the pre- and post-SFAS 141 revision periods, we can assess whether the revision was associated with an improvement in reporting quality. In particular, our examination permits us to assess whether the valuation coefficients of acquired intangibles differ between the two periods, and therefore potentially shed light on the question whether the FASB-intended improvement was perceived as such by equity investors.

We begin our study by investigating the value relevance of definite and indefinite acquired intangible assets. In particular, we assess whether the coefficients of definite and indefinite intangible assets are both statistically and economically different from zero and from each other. A key motivation for this test is to assess whether application of managerial discretion affects an asset's value relevance. In particular, whereas definite intangibles are amortized, indefinite intangibles are subject to annual impairment testing, which requires managerial discretion. Findings reveal that although both definite and indefinite intangible assets are significant in explaining stock prices, definite intangible assets have significantly larger valuation coefficients. These findings are consistent with investors discounting indefinite intangibles relative to definite intangibles when valuing a firm's equity, which suggests that investors find recognized amounts for indefinite-lived assets to be less reliable.

Findings regarding the pre- and post SFAS 141 revision periods reveal that coefficients for definite and indefinite intangibles significantly decline after the revision of SFAS 141. This finding suggests that the provision of more disclosures about valuation methods and inputs led to revised expected cash flow and/or risk assessments yielding an overall downward revision in investors' assessments of the value of definite- and indefinite intangibles. To identify the prevalent channel regarding the source of the downward revision in coefficients, we test whether autoregressive parameters associated with each intangible asset are lower in the post SFAS 141 revision period relative to pre-period. Findings reveal that persistence parameter estimates in the pre- vs post period generally are not significantly different, which suggests that observed decreases in valuation relevance coefficients are attributable to investors revising their risk assessment upwards rather than downward revisions in expected cash flow.

We next extend our analyses by investigating the value relevance for four different intangible asset classes, i.e., tech-, customer-, contract-, and marketing-related intangible assets. We predict and find positive associations with stock prices for all four intangible asset classes. Consistent with prior research on business combinations and innovation (e.g. Bena and Li 2014), purchased tech-related intangible assets have the largest valuation coefficients among all intangible assets. This suggests that investors believe acquired tech intangibles such as patents or trade secrets are likely to bring the greatest benefits to the firm. As with tests relating to aggregate definite and indefinite intangibles, we find that the revision of SFAS 141 is associated with a decrease in valuation coefficients for tech intangibles. Customer-, contract-, and marketing intangibles are also relevant in valuing equities, but they exhibit lower valuation coefficients compared to tech intangibles, which is consistent with investors viewing them as having generally shorter economic lives and lower risk-adjusted economic payoffs than tech-related intangibles. Also, consistent with results for aggregated intangible assets, we find significantly lower coefficients for the post-period.

Next, we test whether the valuation characteristics of the four intangible asset classes differ depending on whether they are classified as having definite and indefinite useful lives.[3] Consistent with our results for aggregated intangible assets, we find that tech- and contract intangibles with definite lives have higher valuation coefficients than those with indefinite lives. The analysis of tech intangibles with regard to their economic lifetime is more subtle, because the split into definite and indefinite useful lives for tech intangibles is only available in the post SFAS 141R revision period because SFAS 141R required for the first time the recognition of

[3] We cannot disaggregate customer intangibles into definite and indefinite because they only have a definite lifetime.

in-process R&D as an indefinite asset. Taken together the findings indicate that each intangible asset class acquired —regardless of economic life— is value relevant to equity investors.

Lastly, to provide evidence on the question of whether particular acquired intangible assets identified by the FASB should be subsumed into goodwill, we separately investigate the value relevance of two intangible assets —customer-related intangible assets and non-compete agreements (NCA).[4] In 2014, the FASB issued a ruling allowing *private* firms to subsume both intangible groups into the goodwill. A recent FASB discussion paper states that it is considering extending this ruling to *public* firms (FASB, 2019), with the implication that valuations of customer intangibles and NCAs are too unreliable for them to be recognized separately. Although we find customer-related intangible assets are positively and significantly associated with equity prices, we find no association between NCAs and stock prices. These results provide empirical support for continuing to recognize customer-related intangibles recognized separately from goodwill because they provide value-relevant information to investors.

Our paper contributes to two strands within the accounting literature. First and most importantly, we contribute to the long-standing debate about the relevance and reliability regarding the role of intangible assets for equity investors. Although there is a substantial literature on the costs and benefits of capitalizing internally generated intangible assets, empirical evidence on acquired intangible assets is limited, mainly because of data availability. Whereas contemporaneous related studies investigate the profitability forecasting ability and value relevance of fair values of acquired intangibles in business combinations only at the time of acquisition, we investigate the value relevance of net amounts of acquired intangibles over a long period from 2002 to 2018 using firm-panel data that include fair values of intangibles from business combinations and individual transactions that reflect amortization and potential impairments. Furthermore, because our sample data also include information regarding the

[4] Non-compete agreements represent employee restrictions that prohibit departing employees from joining or starting a competing enterprise (Starr et al. 2020). NCAs belong to the broad class of marketing intangibles.

economic life for various intangible asset classes, we can address how these intangible asset characteristics affect how investors value intangible assets, and therefore enable us to provide direct evidence regarding the current debate on modifying intangible asset accounting.

Second, we contribute to the debate on the usefulness of historical costs vs. fair value amounts in standard setting. Although there is a large literature that examines the value relevance of fair values for financial instruments, less is known about the value relevance of non-financial assets, and in particular intangible assets. Although other studies provide evidence of forecasting or value relevance of fair values from purchase price allocation data regarding customer and trademark intangibles, our study provides comprehensive evidence that the net amounts of many acquired intangible assets are value relevant for equity investors over time, i.e., at annual reporting dates subsequent to the acquisition date.

The remainder of the paper is organized as follows. Section 2 discusses the institutional framework, related literature, and our predictions. Section 3 presents our research design, section 4 describes our hand collected sample and data, and section 5 presents our results. Finally, section 6 provides concluding remarks.

2. Institutional background, related literature and predictions

2.1 Institutional Background

Standard setters define intangible assets as non-financial assets that lack physical substance (ASC 350; IAS 38). Although many internally generated intangibles such as research and development (R&D) and advertising expenditures are expensed when incurred, acquired intangible assets from individual transactions or business combinations are capitalized on the statement of financial position and amortized or tested for impairment over time. Below, we provide a brief review of the current accounting model for acquired intangible assets, as well as a summary of views regarding their recognition.

In 2001, the FASB issued two standards, SFAS 141 and 142, which substantially changed intangible asset accounting. Notably, SFAS 141, which updated the accounting for business combinations, requires most acquired intangibles be recognized as assets (Guo et al. 2019). Prior to SFAS 141, firms could apply either the pooling of interest or the purchase method for accounting of acquired businesses depending on the target's condition and the form of payment. The "pooling of interests" method does not require acquirers to restate internally generated intangible assets of the target. As a result, under this method, acquired intangibles were not capitalized on the statement of financial position of the acquirer, except for individually acquired intangibles that were recognized at their historical cost.

SFAS 141 and 142 eliminated the pooling of interest method and require acquirers to use the "purchase method" only. Under the purchase method, acquiring firms restate all of the target's assets and liabilities to fair value and record the residual of net assets and the purchase price as goodwill. For intangible assets, this means that acquirers have to identify and estimate fair values of the target's assets. Intangible assets are identifiable when they are contractible (contractual or legal criterion) or separable from the entity (separability criterion) (ASC 805 and 820). A purchased patent is an identifiable intangible asset because it is contractible given its legal nature and can be sold individually. In contrast, merger synergies are not identifiable intangible assets because they are not contractible and cannot be separated from the firm.

Taken together, passage of SFAS 141 resulted in acquiring firms adding billions of dollars of intangible assets in the form of intellectual capital onto the statement of financial position (McInnis and Monsen 2021). Although a benefit of this standard to financial statement users, particularly investors, lies in an increase in information about intangible assets, it also creates a cost by introducing measurement errors of these newly recognized assets on the statement of financial position (Kanodia et al. 2004; McInnis and Monsen 2021). Although standard setters provide guidance on recognizing and valuing intangibles from business combinations (FASB, 2001; FASB 2014), fair values of identifiable intangibles still have to be estimated based on the application of unverifiable assumptions and managerial discretion.

In 2007, the FASB revised SFAS 141 to improve reporting and disclosure requirements regarding the accounting for business combinations. This revision resulted in notable changes in accounting for business combinations (Andrews et al. 2007). With regard to acquired intangibles, SFAS 141R mandates acquiring firms to capitalize in-process R&D (IPRD) as an indefinite intangible asset until the completion or abandonment of the purchased R&D project. Before the revision, IPRD was the only intangible that was excluded from the capitalization requirement. Expensing of IPRD has been justified, given that it cannot reliably stated whether unfinished technology can be completed by the purchasing firm (Healy et al. 2002).

In response to concerns raised by private firms about the appropriate measurement along with high costs of valuing acquired intangible assets, the FASB relaxed acquired intangible asset accounting for private firms in 2014 by issuing *Accounting Standards Update (ASU) No. 2014-18, Business Combinations*. Many private firms raised concerns that costs associated with valuing certain intangible assets such as certain customer-related intangibles and non-compete agreements (NCA) outweigh the benefits for recognizing them separately (FASB 2014). For example, firms claimed that entities can reduce costs for valuing and auditing of these two intangibles when they were allowed to be subsumed into the goodwill. As a consequence, Statement *ASU No. 2014-18* permits private firms to subsume those two intangible assets into the goodwill.[5]

Currently, the FASB is debating whether this accounting update should be applicable to public firms as well and issued a proposal to discuss an extension of current accounting standards update from *private* to *public* entities (FASB 2019). In response to its request for comment on its Exposure Draft, *Identifiable Intangible Assets and Subsequent Accounting for Goodwill*, the Board received over 100 comment letters from financial statement preparers, valuation- and industry experts, and academics with different opinions on current standards and

[5] This accounting standards update also permits private firms to amortize goodwill rather than subject goodwill to annual impairment testing (FASB 2014).

how best to improve them.[6] Proponents of the current accounting model suggest that "measurement of recognized intangible assets is generally reliable and auditable" (Houlihan Loukey 2019). Opponents contend that the valuation of certain acquired intangible assets is associated with high valuation costs for firms and estimated amounts are not useful for investors. In particular, fair values of acquired intangible assets from business combinations need to be estimated and audited, which creates higher monitoring costs for financial statement preparers compared to tangible assets. Moreover, evidence suggests that managers exploit their discretion, which can lead them to overstate valuations for indefinite intangibles to boost short-term earnings (Shalev et al. 2013; Koonce et al. 2020). Several firms even propose to subsume certain intangibles into goodwill, which is not amortized but instead is subject to impairment.[7]

2.2 Related Literature and Predictions

Regarding the value relevance of internally generated intangibles such as R&D, extant accounting research provides a mixed message. Although some studies provide evidence of relevance of intangible assets for investors and suggest that standard setters should allow the capitalization of R&D and advertising expenditures (e.g. Lev and Sougiannis 1996; Kimbrough 2007; Banker et al. 2019), other studies (e.g., Healy et al. 2002) counter that unverifiable intangible amounts decrease the informativeness of financial statement amounts. Because acquired intangible assets result from a market transaction, many, including the FASB and IASB, express the belief that measurement of acquired intangibles from business combinations is likely to be more reliable —and therefore more informative to financial statement users— than measurement of internally generated intangibles. However, others contend that acquired intangibles are no more likely to be useful to financial statement users because measurement of acquired intangibles is based on unverifiable estimates of their future payoffs (Kanodia et al.

[6] Comment letters can be found following the link:
https://www.fasb.org/jsp/FASB/CommentLetter_C/CommentLetterPage&cid=1218220137090&project_id=2019-720&page_number=1.

[7] For example, in its comment letter, T-Mobile proposes that the standard setters should "consider a model in which finite lived intangible assets are subsumed in goodwill."

2004). This is because acquired intangibles are unique and lack an appropriate set of "comparables" against which to benchmark their fair values, markets for them are highly illiquid, and their fair values are estimated using private information about unobservable inputs (Koonce et al. 2020).

As a first step towards addressing whether recognized acquired intangible amounts are potentially useful to financial statement users, including investors, McInnis and Monsen (2021) investigates the cash flow forecasting ability of acquired intangible asset fair values from business combinations using a proprietary database relating to approximately 3,500 distinct business combinations. The same database is used by King et al. (2021) to investigate the importance of intangible asset fair values at the date of acquisition in explaining stock prices using a value relevance framework. Ewens et al. (2020) measures off-balance intangible assets using disclosures from purchase price allocations collected from 10-K's, 10-Q`s, and 8-K's. An important feature of those three studies is that they use fair values from the purchase price allocation of M&A deals. This feature limits the generalizability of the studies' findings for three reasons.

First, examining value relevance of fair values of acquired intangibles at dates beyond the acquisition date is limited without adjusting acquisition date allocation amounts for subsequent amortization and impairments. Moreover, prior literature suggests that stock prices of acquirers are inflated within the year of acquisition, which might confound inferences in a value relevance setting (Harford 2005; McInnis and Monsen 2021).[8] Second, only 81 percent of public deals are disclosed within firm reports (Ewens et al. 2020). Thus, significant amounts of intangibles acquired through public and most importantly private business combinations likely are

[8] Both King et al. (2021) and McInnis and Monsen (2021) acknowledge possible limitations in their studies' research design, including the fact that examining using price allocation data does to address value relevance of acquired intangibles limits such an analysis to the date of acquisition and not subsequent dates. McInnis and Monsen (2021) addresses this limitation by employing a research design that explores the benefits of incorporating intangible assets in forecasting operating income. However, standard setting questions generally relate to empirical tests in equity markets because equity investors are the main recipient of financial statements (Barth et al., 2001). Time series variation on the firm level, however, is critical for studies on acquired intangible assets as post-merger equity prices are inflated, which distorts inferences (Harford 2005; McInnis and Monsen 2021).

excluded, and it is unclear whether valuation properties of the data used in these studies generalize to all acquired intangibles. Third, intangible assets can also be acquired individually and not as part of a business combination. Although this is a minor source of acquired intangibles for firms in some industries, for firms in industries such as telecommunication, intangible assets acquired individually by, e.g., purchasing FCC licenses (e.g., radio, television, wire, satellite, and cable licenses) are a significant portion of their value. In contrast, our study examines the value relevance of net amounts of all acquired intangibles, including those from private deals and those acquired individually, and at all dates rather than just at the acquisition date.

Thus, our study's research setting differs from that of these previous studies by investigating properties of net amounts of acquired intangible assets disclosed in financial statements rather than the properties of acquired intangibles at acquisition dates. We evaluate the usefulness of those net amounts using a value relevance framework (Barth et al. 2001). In our setting, we attribute value relevance to accounting amounts of acquired intangible assets that are significantly positively associated with equity market values, i.e., those with positive valuation coefficients (Amir et al. 1993; Barth et al. 2001).

We begin by investigating the value relevance of definite and indefinite intangible assets. Definite intangible assets are amortized over their economic lifetime (ASC 350). Economic lifetime can either be determined by a contract- or legal period. For instance, the economic lifetime of patents is given by their duration until expiration date. King et al. (2021) finds initial evidence in the context of the study's organic and wasting intangible asset design that definite intangible assets are value relevant for equity investors.[9] In contrast, indefinite intangible assets are not amortized over the economic lifetime, and are subject to annual impairment testing. The

[9] King et al. (2021) defines "wasting intangibles" as "separable from the firm with legally defined contractual lives". According to them, technology- and contract intangibles belong within this category. Organic intangibles, on the other hand, are defined as intangibles with "significant expenditures to enhance/maintain its value". This category is the sum of customer- and marketing intangibles.

most common indefinite intangible is goodwill. Although there is a substantive literature on goodwill accounting (e.g., Li and Sloan 2017; Glaum et al. 2018), less is known about other indefinite intangible assets. Other indefinite intangible assets can be acquired trademarks, licenses and purchased in-process research and development (IPRD).

On the one hand, we might expect indefinite intangibles not to be value relevant because their accounting amounts are subject to greater measurement error arising from managerial discretion. For instance, CEOs that are closer to retirement and have bonus packages linked to firm's earnings performance allocate a greater proportion to indefinite intangible assets (Shalev et al. 2013). Additionally, untimely recognition of impairment losses could make net amounts unreliable to equity investors. On the other hand, indefinite intangibles such as a trademark can be valuable for firms as their payoffs last longer than payoffs from definite intangible assets. Thus, we test for the value relevance of definite and indefinite intangible assets separately and formulate the following hypothesis, stated in terms of the null, with regard to definite and indefinite intangibles:

Hypothesis 1a: Valuation coefficients for definite and indefinite intangible assets are not significantly different from zero.

Next, we investigate whether valuation coefficients differ before and after the revision of SFAS 141. The revision of SFAS 141, effective for the fiscal years after 2008, aims to improve the accounting for acquired intangibles in business combinations. In particular, the revision is designed to provide more guidance on valuation inputs and models used, especially for indefinite intangibles. The revision of SFAS 141 also enhanced impairment test disclosures to resolve uncertainties for equity investors. Conducting our valuation tests separately for sample years before and after the revision could provide evidence on the effectiveness of this mandate if we find altered and more significant coefficients for those intangibles likely most affected by the standard's revision. For instance, we could find higher coefficients when more disclosures improve the overall information quality about acquired intangible assets (Barth 1991). This effect would be attributable to a better risk assessment of acquired intangibles. On the other hand, we could find lower coefficients for definite and indefinite intangibles within the post period if investors revise their expected cash flows downwards based on the new disclosure regime. Therefore, size and magnitude of the estimated coefficients will depend on which effect is more prevalent. Hence, we test the following hypothesis:

Hypothesis 1b: Valuation coefficients for definite and indefinite intangible assets do not change after the revision of SFAS 141.

Next, we investigate the value relevance of different intangible asset classes. In their frameworks, both the FASB and IASB define five intangible asset classes: tech, customer, contract, marketing and artistic.[10] Relevance for investors of intangible asset classes can differ depending on their duration and reliability of their underlying future payoffs.

The first category, tech-related intangible assets (or tech intangibles) include patents, developed technology or software and are core factors that affect a firm's competitive position within its industry. Internally generated tech-related intangible assets, which roughly are approximated in many prior studies by R&D expenditures and patents, are believed to be among the most valuable assets within a firm (e.g. Lev and Sougiannis 1996; Hall et al. 2005). Empirical evidence for the relevance of acquired tech intangibles, however, is rather mixed. On the one hand, research shows that acquired technology such as patents are a major source of merger synergies and ex-post stock returns (Bena and Li 2014; Lys and Yehuda 2016; Beneish et al. 2020; Guo et al. 2019). On the other hand, McInnis and Monsen (2021) finds no association between fair values of acquired tech intangibles and future operating income, suggesting that accounting amounts of tech intangibles are not forecasting relevant because of their high unreliability.

[10] Artistic-related intangible assets represent plays, books, paintings, pictures, and song records. In our investigation, we abstract from artistic-related intangibles since there are rather concentrated among a few subindustries and rather of low economic relevance for firms (Guo et al. 2019). Thus, artistic intangibles are included within the category "other." See the appendix for more information.

The second category consists of customer-related intangible assets (or customer intangibles). This group contains items such as customer lists and -relationships and customer-ordered backlog. Customer-related intangibles are a significant part of each M&A deal volume (Beneish et al. 2020). Bauman and Shaw (2018) provides empirical evidence for a sample of 200 firms that acquired customer intangibles are value relevant. McInnis and Monsen (2021) finds that customer intangibles contain predictive ability for future cash flows even up to five years after acquisition. In contrast, Dikolli et al. (2007) suggests that the importance and value of customer intangibles depends critically on industry specific characteristics such as varying switching costs for customers. Many practitioners even contend that customer intangibles are associated with higher valuation costs and provide low benefits to equity investors.[11]

The third category, contract-related intangible assets (or contract intangibles), contain many non-customer contractual relationships such as franchises, licenses, management agreements, favorable leases, and water-, land- and emission rights. Galasso et al. (2013) and Kim-Gina (2018) provide descriptive evidence that licenses are a valuable avenue to acquire intellectual capital. Apart from licenses, a few industry-specific studies investigate the importance of contract intangibles such as airport landing rights or franchises (Bonacchi et al. 2015; Olbrich et al. 2009). However, we are unaware of any study investigating value relevance of this whole category across a broad sample.

The last category comprises marketing-related intangible assets (or marketing intangibles), which consists mostly of trademarks and tradenames, brands, mastheads, and non-compete agreements. Prior research documents that internally generated brands are positively associated with stock prices (Barth et al. 1998, Kallapur and Kwan 2004; Vitorino 2014). Furthermore, acquired trademarks are associated with higher synergies (Beneish et al. 2020; Hsu et al. 2018). However, McInnis and Monsen (2021) finds only a weak association between fair values of

[11] For instance, Exelon Inc. claims that these assets do not provide any “useful information to investors as they are not typically sold separately” (Exelon 2019).

trademarks and future profitability of the combined firm. Among practitioners, several firms such as LSC Communications suggest in their comment letters to the FASB that acquired trademarks could even be subsumed into the goodwill because they "carry little future cash flow[s] apart from the business processes that built that trade name."[12]

Taken together, we formulate the following hypothesis with regard to tech, customer, contract, and marketing:

Hypothesis 2a: Tech-, customer-, contract, and marketing intangibles valuation coefficients are not significantly different from zero.

Next, we investigate valuation coefficients for those intangible asset classes before and after the revision of SFAS 141. The revision should be, in particular, relevant for tech intangibles because it mandates capitalization of acquired in-process research and development (IPRD) expenditures. The revision will likely also alter valuation coefficients for other intangible asset classes (customer, contract, marketing) because it should provide more guidance on valuation inputs and models used. Coefficients can be either higher or lower than in the pre-period depending on the expected cash flow/risk assessment of equity investors. In particular, coefficients can be higher in the post period if additional guidance reduces investors' assessment of risk, or lower if the guidance leads to higher assessments of future cash flow. Our hypothesis is the following:

Hypothesis 2b: Valuation coefficients for tech-, customer-, contract-, and marketing intangibles do not change after the revision of SFAS 141.

Third, we investigate the value relevance of our four different intangible asset classes disaggregated into definite and indefinite-live intangible assets. This allows us to assess whether the value relevance of assets within each asset class is affected by whether assets are

[12] See link for comment letter of LSC Communications Inc.: https://www.fasb.org/cs/BlobServer?blobkey=id&blobnocache=true&blobwhere=1175836064236&blobheader=application%2Fpdf&blobheadername2=Content-Length&blobheadername1=Content-Disposition&blobheadervalue2=1522933&blobheadervalue1=filename%3DINTANGGW.ITC.081.LSC_COMMUNICATIONS_SEE_LISTED.pdf&blobcol=urldata&blobtable=MungoBlobs.

classified as having a definite or indefinite life. For instance, customer- and contract intangibles are of rather short duration in comparison to tech- and marketing intangibles. Thus, different economic lifetimes create uncertainties with regard to their future payoffs. Thus, we test the following hypothesis:

Hypothesis 3a: Valuation coefficients for tech-, customer-, contract-, and marketing intangibles disaggregated into definite and indefinite intangibles are not significantly different from zero.

Next, we investigate valuation coefficients for disaggregated intangible asset classes before and after the revision of SFAS 141. A particular interesting property of this test is the evaluation of the capitalization of in-process R&D (IPRD) after the revision of SFAS 141. Deng and Lev (2006) investigates whether IPRD should be recognized as an asset or expensed and provides evidence of a significant positive association between the values of in-process R&D and acquiring firms' cash flows supporting the recognition of IPRD as an asset. On the other hand, Chung et al. (2019) finds no empirical evidence that the capitalization of IPRD in 2008 led to lower information asymmetries for IPRD acquirers relative to non-IPRD acquirers. For other indefinite intangibles such as contract- and marketing intangibles, we predict that the revision alters valuation coefficients as firms should provide more guidance on valuation inputs and models used for indefinite intangibles. In particular, coefficients can be higher for the post period if the additional guidance reduces risk, while lower coefficients apply that cash flow expectations are better assessable. Thus, we test the following hypothesis:

Hypothesis 3b: Valuation coefficients for tech-, customer-, contract-, and marketing intangibles disaggregated into definite and indefinite intangibles do not change after the revision of SFAS 141.

Lastly, we investigate one critical aspect of the current FASB proposal, the inclusion of two particular intangible asset groups into goodwill, namely customer intangibles and non-compete agreements (NCAs). In 2014, the FASB passed *Accounting Standards Update (ASU)*

No. 2014-18, *Business Combinations*, allowing *private* companies to subsume customer intangibles and non-compete agreements (NCAs) into goodwill. With the passage of this *ASU No. 2014-18,* the FASB stated that customer-related intangibles and non-compete agreements "will continue to provide decision-useful information to the users of private company financial statements while providing a reduction in the cost and complexity associated with the measurement of certain identifiable intangible assets" (FASB 2014). Currently, the FASB is considering extending this rule change to apply to public firms. As noted earlier, proponents of this accounting proposal contend that the valuation of these intangible assets is associated with higher costs for monitoring and auditing for financial statement preparers.

Non-compete agreements (NCAs) are employee restrictions that prohibit departing employees from joining or starting a competing enterprise (Starr et al., 2020).[13] Although the use of NCAs for employees has increased in recent years for firms in many industries (Starr et al., 2020), valuation experts contend that NCAs provide little to no benefits to investors. However, there is no direct evidence on the valuation relevance of non-compete agreements. Several studies, however, find indirect evidence for the importance of non-compete agreements exploring different enforcement regimes (Aobdia 2018; Ertimur et al. 2018; Glaeser 2018). For example, managers pursue riskier innovative activities (Samila and Sorenson 2011; Conti 2014) when NCAs are enforceable, which could result in a better competitive advantage position and higher market values in the case of innovative success. Thus, our hypothesis with regard to customer intangibles and non-compete agreements is the following (stated in terms of the null):[14]

Hypothesis 4: Customer intangibles and non-compete agreements are not significantly different from zero.

[13] Non-compete agreements are a subcategory of marketing intangibles.
[14] We do not test for a change in SFAS 141R, because customer intangibles and non-compete agreements were not subject of major changes. Hence, there is no hypothesis 4b.

3. Research design

3.1 Baseline model

Following Barth et al. (1999, 2005) we test our predictions in a generalized version of the Ohlson (1999) model. The basic model comprises the following four equations:

$$\begin{aligned}
Abearnings_{t+1} &= Abearnings_t + Accruals_t + BVE_t + e_{1t+1} && (1)\\
Accruals_{t+1} &= Accruals_t + BVE_t + e_{2t+1} && (2)\\
BVE_{t+1} &= BVE_t + e_{3t+1} && (3)\\
MVE_t &= BVE_t + Abearnings_t + Accruals_t + e_{4t+1} && (4)
\end{aligned}$$

Equation (1) models the autoregressive process for abnormal earnings, in which *Abearnings* represent earnings less a normal return on equity book value (*BVE*). Equation (2) models the process for the accruals component of earnings, *Accruals*. Both equations (1) and (2) include book value of equity (*BVE*), which allows the effects of conservatism to manifest themselves (Feltham and Ohlson 1995; 1996) and relaxes the assumption that the cost of capital is a predetermined cross-sectional constant (Barth et al. 1999; 2005). Equation (3) models the information dynamics of the book value of equity as an autoregressive process. This equation preserves the triangular information structure of the generalized version of Ohlson's (1999) model, which permits the equity valuation equation coefficients in equation (4) to be expressed as functions of the autoregressive and forecasting equation coefficient in equations (1) through (3). Equation (4) models our main equation of interest, the valuation equation. Market value of equity can be explained by book value of equity, abnormal earnings, and accruals. Below, we expand the basic system of equations to include acquired intangibles to test our main predictions. For the baseline model and each of the adjusted models described below, the equity valuation coefficients can be freely estimated, i.e., unconstrained, or estimated in a constrained system that imposes the implied relations between the valuation coefficients and the autoregressive and forecasting equation coefficients.

3.2 Value relevance of definite and indefinite intangible assets

We adjust the baseline Ohlson (1999) model to allow testing our predictions. For our first set of predictions, we extend the baseline model by including acquired definite- and indefinite intangible assets. First, we extend the abnormal earnings- and earnings component equations by definite and indefinite intangible assets. Second, we append autoregressive processes for both definite and indefinite intangible assets to preserve the triangular information structure. Third, we model market value of equity as a composition of book value, abnormal earnings, earnings components, and definite and indefinite intangible assets. Thus, our adjusted model comprises the following six equations (*System 1*):

$$Abearnings_{t+1} = \alpha_1 + \omega_{11} Abearnings_t + \omega_{12} Accruals_t + \omega_{13} BVE\_adj_t + \omega_{14} Def\_\text{int}_t + \omega_{15} Indef\_\text{int}_t + e_{1t+1} \quad \text{(1a)}$$

$$Accruals_{t+1} = \alpha_2 + \omega_{22} Accruals_t + \omega_{23} BVE\_adj_t + \omega_{24} Def\_\text{int}_t + \omega_{25} Indef\_\text{int}_t + e_{2t+1} \quad \text{(1b)}$$

$$BVE\_adj_{t+1} = \alpha_3 + \omega_{33} BVE\_adj_t + e_{3t+1} \quad \text{(1c)}$$

$$Def\_\text{int}_{t+1} = \alpha_4 + \omega_{44} Def\_\text{int}_t + e_{4t+1} \quad \text{(1d)}$$

$$Indef\_\text{int}_{t+1} = \alpha_5 + \omega_{55} Indef\_\text{int}_t + e_{5t+1} \quad \text{(1e)}$$

$$MVE_t = \alpha_6 + \beta_1 BVE\_adj_t + \beta_2 Abearnings_t + \beta_3 Accruals_t + \beta_4 Def\_\text{int}_t + \beta_5 Indef\_\text{int}_t + e_{6t+1} \quad \text{(1f)}$$

We adjust equity book values by subtracting acquired intangible assets (*BVE_adj*). The key variables of interest, *Def_int* and *Indef_int*, are net amounts of definite and indefinite intangible assets. Equations (1c) to (1e) model *BVE_adj*, *Def_int* and *Indef_int* as autoregressive processes. Equation (1f) models our valuation equation containing *Def_int* and *Indef_int*. Based on H1a, we test whether the *Def_int and Indef_int* coefficients are significantly different from zero.

3.3 Value relevance of tech, customer, contract, and marketing intangible assets

For our second set of predictions, we extend the baseline model and include tech-, customer-, contract-, and marketing-related intangible assets in the same manner as specified above. To testing our predictions relating to H2a, our model comprises the following nine equations (*System 2*):

$$Abearnings_{t+1} = \alpha_1 + \omega_{11} Abearnings_t + \omega_{12} Accruals_t + \omega_{13} BVE\_adj_t + \omega_{14} Tech_t + \omega_{15} Customer_t + \omega_{16} Contract_t + \omega_{16} Marketing_t + \omega_{17} Other_t + e_{1t+1} \quad (2a)$$

$$Accruals_{t+1} = \alpha_2 + \omega_{22} Accruals_t + \omega_{23} BVE\_adj_t + \omega_{24} Tech_t + \omega_{25} Customer_t + \omega_{26} Contract_t + \omega_{27} Marketing_t + \omega_{28} Other_t + e_{2t+1} \quad (2b)$$

$$BVE\_adj_{t+1} = \alpha_3 + \omega_{33} BVE\_adj_t + e_{3t+1} \quad (2c)$$

$$Tech_{t+1} = \alpha_4 + \omega_{44} Tech_t + e_{4t+1} \quad (2d)$$

$$Customer_{t+1} = \alpha_5 + \omega_{55} Customer_t + e_{5t+1} \quad (2e)$$

$$Contract_{t+1} = \alpha_6 + \omega_{66} Contract_t + e_{6t+1} \quad (2f)$$

$$Marketing_{t+1} = \alpha_7 + \omega_{77} Marketing_t + e_{7t+1} \quad (2g)$$

$$Other_{t+1} = \alpha_8 + \omega_{88} Other_t + e_{8t+1} \quad (2h)$$

$$MVE_t = \alpha_9 + \beta_1 BVE_t + \beta_2 Abearnings_t + \beta_3 Accruals_t + \beta_4 Tech_t + \beta_5 Customer_t + \beta_6 Contract_t + \beta_7 Marketing_t + \beta_8 Other_t + e_{9t+1} \quad (2i)$$

We include *Tech*, *Customer*, *Contract*, and *Marketing* as independent variables in the first two autoregressive processes (equation (2a) and (2b)). Additionally, we model each intangible class as an additional autoregressive process (equation (2c) to (2h)). For intangibles, which we cannot assign to one of these categories, we include a variable *Other* as both an independent variable and an autoregressive process in our model.[15] Equation (2i) models the valuation equation with our main variables of interest. In particular, we test whether the *Tech, Customer, Contract*, and *Marketing* coefficients are significantly different from zero.

3.4 Value relevance of disaggregated intangible assets

Third, we extend our baseline model for the previous four intangible asset classes (tech-, customer-, contract-, and marketing) disaggregated into definite and indefinite economic lifetimes. Customer intangibles are usually of definite lifetime, which is why we model them as one process only. Below, we present the adjusted equation system with the following twelve equations that we use to test H3a (*System 3*):

[15] Further information on the inclusion of items and representativeness of this category are provided within the sample and data section.

$$Abearnings_{t+1} = \alpha_1 + \omega_{11} Abearnings_t + \omega_{12} Accruals_t + \omega_{13} BVE\_adj_t + \omega_{14} Tech\_Def_t + \omega_{15} Tech\_Indef_t + \omega_{16} Customer_t + \omega_{17} Contract\_Def_t + \omega_{18} Contract\_Indef_t + \omega_{19} Marketing\_Def_t + \omega_{\_10} Marketing\_Indef_t + \omega_{\_11} Other_t + e_{1t+1} \tag{3a}$$

$$Accrual_{t+1} = \alpha_2 + \omega_{22} Accrual_t + \omega_{23} BVE\_adj_t + \omega_{24} Tech\_Def_t + \omega_{25} Tech\_Indef_t + \omega_{26} Customer_t + \omega_{27} Contract\_Def_t + \omega_{28} Contract\_Indef_t + \omega_{29} Marketing\_Def_t + \omega_{\_20} Marketing\_Indef_t + \omega_{\_21} Other_t + e_{2t+1} \tag{3b}$$

$$BVE\_adj_{t+1} = \alpha_3 + \omega_{33} BVE\_adj_t + e_{3t+1} \tag{3c}$$

$$Tech\_Def_{t+1} = \alpha_4 + \omega_{44} Tech\_Def_t + e_{4t+1} \tag{3d}$$

$$Tech\_Indef_{t+1} = \alpha_5 + \omega_{55} Tech\_Indef_t + e_{5t+1} \tag{3e}$$

$$Customer_{t+1} = \alpha_6 + \omega_{66} Customer_t + e_{6t+1} \tag{3f}$$

$$Contract\_Def_{t+1} = \alpha_7 + \omega_{77} Contract\_Def_t + e_{7t+1} \tag{3g}$$

$$Contract\_Indef_{t+1} = \alpha_8 + \omega_{88} Contract\_Indef_t + e_{8t+1} \tag{3h}$$

$$Marketing\_Def_{t+1} = \alpha_9 + \omega_{99} Marketing\_Def_t + e_{9t+1} \tag{3i}$$

$$Marketing\_Indef_{t+1} = \alpha_{10} + \omega_{\_101} Marketing\_Indef_t + e_{10t+1} \tag{3j}$$

$$Other_{t+1} = \alpha_{11} + \omega_{\_111} Other_t + e_{11t+1} \tag{3k}$$

$$MVE_t = \alpha_{12} + \beta_1 BVE_t + \beta_2 Abearnings_t + \beta_3 Accrual_t + \beta_4 Tech\_Def_t + \beta_5 Tech\_Indef_t + \beta_6 Customer_t + \beta_7 Contract\_Def + \beta_8 Contract\_Indef_t + \beta_9 Marketing\_Def_t + \beta_{10} Marketing\_Indef_t + \beta_{11} Other_t + e_{12t+1} \tag{3l}$$

Equation (3l) models the valuation equation with our main variables of interest. In particular, we test whether the *Tech_Def*, *Tech_Indef*, *Customer*, *Contract_Def*, *Contract_Indef*, *Marketing_Def*, and *Marketing_Indef* coefficients are significantly different from zero.

3.5 Testing the FASB proposal regarding a change in intangible asset accounting

Lastly, we test our predictions for one aspect of the recent FASB proposal to extend intangible asset accounting of *private* firms to public entities. To test the usefulness of this approach for public firms, we separate non-compete agreements (*NCA*) from other definite marketing intangibles (*Marketing_def_ex*) to test H4 (*System 4*):

$$Abearnings_{t+1} = \alpha_1 + \omega_{11} Abearnings_t + \omega_{12} Accruals_t + \omega_{13} BVE\_adj_t + \omega_{14} Tech\_Def_t + \omega_{15} Tech\_Indef_t + \omega_{16} Customer_t$$
$$+\omega_{17} Contract\_Def_t + \omega_{18} Contract\_Indef_t + \omega_{19} Marketing\_Def\_ex_t + \omega_{19} NCA_t + \omega_{\_10} Marketing\_Indef_t + \omega_{\_11} Other_t + e_{1t+1} \tag{4a}$$

$$Accrual_{t+1} = \alpha_2 + \omega_{22} Accrual_t + \omega_{23} BVE\_adj_t + \omega_{24} Tech\_Def_t + \omega_{25} Tech\_Indef_t + \omega_{26} Customer_t + \omega_{27} Contract\_Def_t$$
$$+\omega_{28} Contract\_Indef_t + \omega_{29} Marketing\_Def\_ex_t + \omega_{\_20} NCA_t + \omega_{\_21} Marketing\_Indef_t + \omega_{\_22} Other_t + e_{2t+1} \tag{4b}$$

$$BVE\_adj_{t+1} = \alpha_3 + \omega_{33} BVE\_adj_t + e_{3t+1} \tag{4c}$$

$$Tech\_Def_{t+1} = \alpha_4 + \omega_{44} Tech\_Def_t + e_{4t+1} \tag{4d}$$

$$Tech\_Indef_{t+1} = \alpha_5 + \omega_{55} Tech\_Indef_t + e_{5t+1} \tag{4e}$$

$$Customer_{t+1} = \alpha_6 + \omega_{66} Customer_t + e_{6t+1} \tag{4f}$$

$$Contract\_Def_{t+1} = \alpha_7 + \omega_{77} Contract\_Def_t + e_{7t+1} \tag{4g}$$

$$Contract\_Indef_{t+1} = \alpha_8 + \omega_{88} Contract\_Indef_t + e_{8t+1} \tag{4h}$$

$$Marketing\_Defex_{t+1} = \alpha_9 + \omega_{99} Marketing\_Def\_ex_t + e_{9t+1} \tag{4i}$$

$$NCA_{t+1} = \alpha_{10} + \omega_{\_101} NCA_t + e_{10t+1} \tag{4j}$$

$$Marketing\_Indef_{t+1} = \alpha_{11} + \omega_{\_111} Marketing\_Indef_t + e_{11t+1} \tag{4k}$$

$$Other_{t+1} = \alpha_{12} + \omega_{\_121} Other_t + e_{12t+1} \tag{4l}$$

$$MVE_t = \alpha_{13} + \beta_1 BVE_t + \beta_2 Abearnings_t + \beta_3 Accrual_t + \beta_4 Tech\_Def_t + \beta_5 Tech\_Indef_t + \beta_6 Customer_t$$
$$+\beta_7 Contract\_Def + \beta_8 Contract\_Indef_t + \beta_9 Marketing\_Def_t + \beta_{10} NCA + \beta_{11} Marketing\_Indef_t + \beta_{12} Other_t + e_{13t+1} \tag{4m}$$

Our variables of interest in the equity valuation equation (4m) are *Customer* and *NCA*, in which we test whether their coefficients are significantly different from zero.

3.6 Estimation of equations

We estimate our four systems using two procedures. First, we estimate each system as an unconstrained model imposing no linear information structure on intangible asset coefficients. Second, we follow Ohlson (1999) and impose a linear information structure on each intangible asset in the valuation equation. Valuation multiples of each intangible asset are therefore determined by the underlying information dynamics in the autoregressive processes. This constrained estimation allows intangible asset coefficients to include not only the concept of value relevance, but also the persistence and forecasting ability of each intangible asset for abnormal earnings and accruals processes. For our first system (*System 1*) this means that signs and magnitudes of definite intangible assets and indefinite intangibles in equation (1f) depend on the signs and magnitudes of particular coefficients in equations (1a) through (1e). We derive our constrained estimators within the online appendix C.[16]

[16] For the sake of parsimony we do not provide additional appendices for the derivation of the constrained equity valuation coefficients for *Systems 2* through *4*. They are available upon request.

For our predictions concerning the SFAS141 revision, we estimate our constrained system as a fully interacted model. This allows us to investigate how the revision of SFAS 141 manifested in intangible asset coefficients. We include both year and industry fixed effects in each equation and specification. Consistent with prior literature, we define industry fixed effects following the Fama-French 49 classification (King et al. 2021).

Abnormal earnings, $Abearnings_t$, equals $NI_t - rBVE_{t-1}$, where *BVE* is equity book value and net income *NI* is income before extraordinary items and discontinued operations. Following prior literature, we set the discount rate, *r*, equal to 12% as it represents the long-term return on equities (Dechow et al. 1999; Myers 1999; Barth et al. 1999). Also consistent with prior literature, we define *Accruals* as the difference between net income and operating cash flows (Barth et al. 1999). We winsorize our dependent and independent variables on 1^{st} and 99^{th} percent level on both time- and industry dimension (Fama-French 12 industry) to mitigate potential outlier effects (Barth et al. 1999). Further, we scale our variables by shares outstanding to mitigate potential scale bias and heteroscedasticity (Barth and Kallapur 1996; Barth and Clinch 2010). Scaling also mitigates non-stationarity concerns in our autoregressive processes (Qi et al. 2000).

Following Barth et al. (1999), we estimate *Systems 1* through *4* using a seemingly unrelated regression design (Zellner 1962; Zellner and Huang 1962; Greene 2012), which permits regression errors to be correlated across equations.

4. Sample and data

We construct our sample by first obtaining accounting- and stock price data from Compustat and CRSP from 2002 until 2018. Our sample begins for fiscal year 2002 because this is the first year for which SFAS 141 and 142 became effective. We require firms to have non-missing equity book values, total assets, stock prices, operating cash flows, and net income. Additionally, we restrict our sample to firms with total assets of more than $10 million to avoid any influence of small firms (Barth et al. 1999). Consistent with prior research, we use a three-month lag window to make sure that new financial statement information is incorporated into equity prices (e.g. McInnis et al. 2018). Lastly, we require a minimum of three observations per firm because we use lagged abnormal earnings in our estimations.

Next, we collect acquired intangible asset *net amounts* from the notes of annual financial statements obtained from the SEC Edgar webpage. To avoid any collection bias towards a certain industry, we choose firms across all industries. We identify industries using the Fama-French (1997) 12-industry classification. Within each industry, we sort the merged Compustat/CRSP sample by market capitalization. Our sample includes those firms within each industry with the largest market capitalization comprising at least 50% of the total industry market capitalization.

We obtain net amounts of acquired intangible asset using a keyword search for words such as "intangible asset," "purchased intangible," and "intangibles" to identify relevant sections of a financial statement, and collect *net amounts* of purchased intangible assets. If net amounts are missing, we calculate net amounts by subtracting accumulated amortization and impairments from disclosed gross amounts. Importantly, we only collect net amounts of intangibles that we can clearly identify as being purchased. Firms sometimes allocate capitalized internally generated software - or patent costs (from legal fees) into the notes about intangible assets in their annual reports. We read each note about intangible assets carefully to make sure that we do not collect these items as they do not relate to our research question. Unfortunately, some firms are not completely transparent about their disclosure of all acquired intangible asset amounts. First, a few firms aggregate several acquired intangible assets into a position called "other intangible assets," thereby restricting the collection of all acquired intangible amounts with full transparency. A second difficulty arises when firms add different intangible asset classes together.[17] Both concerns are mitigated by the fact that these concerns relate to only a

[17] For example, a few firms provide an aggregated position called "patents and trademarks," i.e., adding tech- and marketing intangibles together.

small subsample of our overall sample. We include these amounts as a variable denoted *Other* in our estimating equations and note that *Other* is less than six percent of the total amount of intangibles acquired on average.

Table 1 Panel A presents our sample composition based on Fama-French 12 industry classifications. Our sample includes 16,508 firm year observations relating to 1,647 firms.[18] Industries with the largest concentrations of firm-year observations are Equipment firms (17.62%), Health firms (12.16%), and Shop firms (12.77%).

[18] In 2017, our sample represents more than 65 percent of total market capitalization of the US-stock market.

Table 1: Sample composition and descriptive statistics

Table 1 provides descriptive statistics for the variables used in this study. Panel A an industry composition of our sample. We define industry levels using Fama-French 12 industry classifications. Panel B presents descriptive statistics for independent and dependent variables. All amounts are denoted in $ million. Panel C presents univariate Pearson (below the diagonal) and Spearman (above) correlations between our used variables in this study. All variables are defined in Appendix A.

Panel A: Sample Composition

Industry	N	Firms	Percentage
Nondurables	1651	171	10.00%
Durables	696	73	4.22%
Manufacturing	1544	131	9.35%
Energy	806	80	4.88%
Chemical	816	78	4.94%
Equipment	2908	290	17.62%
Telephone	821	104	4.97%
Utilities	621	51	3.76%
Shops	2108	198	12.77%
Health	2007	225	12.16%
Finance	719	67	4.36%
Other	1811	179	10.97%
Sum	**16508**	**1647**	**100%**

Panel B: Descriptive statistics

Industry	Mean	Median	25%	75%	95%	99%	SD
MVE	10316.09	2218.32	546.50	8407.15	47946.84	147092.77	24123.62
BVE_adj	3322.25	609.06	143.44	2180.50	15089.00	44968.00	12235.81
Abearnings	100.74	1.50	-47.11	111.85	1221.24	3747.00	800.82
Accruals	-475.97	-86.05	-352.44	-13.77	57.70	445.00	1199.32
CFO	991.54	199.45	34.81	771.00	4820.00	13570.00	2344.40
Def_Int	332.68	18.00	0	163.90	1754.00	5117.00	1074.53
Indef_Int	222.65	0	0	21.50	830.00	6609.00	1049.39
Tech	85.63	0	0	8.60	326.00	2234.00	449.52
Tech_Def	74.51	0	0	7.55	285.71	1920.00	368.97
Tech_Indef	5.76	0	0	0	0	169.69	50.42
Customer	92.46	0	0	28.81	533.00	1641.00	288.30
Contract	84.23	0	0	1.12	372.00	2083.65	438.51
Contract_Def	28.01	0	0	0	142.00	710.00	121.60
Contract_Indef	40.02	0	0	0	29.82	1520.41	293.95
Marketing	128.20	0	0	24.00	575.26	3089.00	541.11
Marketing_Def	14.77	0	0	1.12	76.00	377.41	62.01
Marketing_Indef	104.28	0	0	2.50	458.59	2828.00	476.25
NCA	0.49	0	0	0	1.55	12.80	3.51
Other	30.18	0	0	4.35	164.40	591.55	113.04

Panel C: Pearson and Spearman correlations:

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*	*(13)*	*(14)*	*(15)*	*(16)*	*(17)*	*(18)*	*(19)*
MVE (1)		0.766	0.364	-0.624	0.866	0.461	0.201	0.187	0.179	0.140	0.185	0.131	0.115	0.037	0.199	0.080	0.132	-0.091	0.369
BVE_adj (2)	0.666		0.175	-0.525	0.730	0.299	0.039	0.115	0.110	0.077	0.119	0.042	0.056	-0.038	0.087	0.044	0.028	-0.068	0.281
Abearnings (3)	0.493	0.133		0.021	0.380	0.125	0.075	0.033	0.032	-0.005	0.039	0.005	0.010	-0.012	0.109	0.040	0.080	-0.002	0.146
Accruals (4)	-0.647	-0.529	-0.036		-0.754	-0.322	-0.148	-0.089	-0.086	-0.090	-0.112	-0.128	-0.103	-0.079	-0.114	-0.030	-0.075	0.074	-0.247
CFO (5)	0.880	0.659	0.439	-0.833		0.438	0.225	0.121	0.117	0.098	0.184	0.151	0.121	0.078	0.214	0.082	0.155	-0.072	0.360
Def_Int (6)	0.538	0.197	0.187	-0.409	0.506		0.379	0.534	0.528	0.215	0.639	0.365	0.367	0.082	0.538	0.447	0.310	0.153	0.579
Indef_Int (7)	0.438	0.120	0.195	-0.299	0.434	0.470		0.152	0.124	0.279	0.256	0.314	0.150	0.413	0.640	0.116	0.818	0.026	0.283
Tech (8)	0.380	0.076	0.150	-0.262	0.330	0.706	0.303		0.980	0.358	0.413	0.056	0.094	-0.092	0.278	0.347	0.087	0.087	0.161
Tech_Def (9)	0.383	0.080	0.150	-0.271	0.337	0.698	0.279	0.966		0.279	0.416	0.055	0.093	-0.093	0.277	0.356	0.081	0.092	0.152
Tech_Indef (10)	0.237	0.037	0.088	-0.136	0.186	0.531	0.233	0.735	0.621		0.083	0.011	0.032	-0.043	0.055	0.091	0.003	-0.022	0.055
Customer (11)	0.328	0.202	0.074	-0.270	0.327	0.534	0.307	0.164	0.201	-0.006		0.146	0.126	0.064	0.483	0.478	0.263	0.269	0.224
Contract (12)	0.300	0.127	0.085	-0.301	0.341	0.370	0.653	0.138	0.160	0.030	0.279		0.868	0.491	0.190	0.125	0.128	0.062	0.100
Contract_Def (13)	0.240	0.101	0.087	-0.225	0.246	0.334	0.216	0.123	0.128	0.105	0.146	0.471		0.094	0.171	0.143	0.096	0.071	0.067
Contract_Indef (14)	0.219	0.088	0.050	-0.260	0.282	0.256	0.644	0.103	0.127	-0.015	0.274	0.863	0.121		0.071	-0.007	0.097	0.018	0.076
Marketing (15)	0.376	0.117	0.191	-0.209	0.348	0.414	0.709	0.166	0.153	0.134	0.289	0.225	0.201	0.178		0.634	0.751	0.279	0.279
Marketing_Def (16)	0.277	0.101	0.094	-0.190	0.246	0.440	0.260	0.249	0.268	0.150	0.382	0.115	0.115	0.093	0.422		0.119	0.496	0.098
Marketing_Indef(17)	0.347	0.104	0.182	-0.179	0.319	0.347	0.716	0.124	0.111	0.095	0.268	0.230	0.202	0.184	0.964	0.262		0.053	0.234
NCA (18)	0.000	-0.003	0.002	0.000	-0.001	0.022	-0.015	-0.015	-0.014	-0.015	0.074	0.005	0.057	-0.013	0.010	0.111	-0.004		-0.062
Other (19)	0.431	0.217	0.217	-0.295	0.408	0.501	0.310	0.234	0.222	0.183	0.171	0.216	0.104	0.185	0.296	0.160	0.281	-0.011	

Panel B presents descriptive statistics for the variables we use in our regressions. The mean (median) market capitalization for our sample firms is $10,316 million ($2,218 million). Our average firm has $128 million in marketing-, $92 million in customer-, $86 million in tech-, and $84 million in contract-intangibles. Panel C, which presents both Pearson and Spearman correlation of our variables, reveals that many variables are highly correlated, which is consistent with prior valuation studies (e.g., Barth et al. 1999).

5. Results

5.1. Definite and indefinite intangible assets

Table 2, Panel A, presents findings for *System 1*. Columns 1 and 2 present findings for the full sample based on unconstrained and constrained estimations. Columns 3a and 3b present pre- and post-SFAS 141 revision period coefficients based on a constrained estimation that includes a post-indicator variable and its interaction with all regression variables. Column 3c presents the coefficient differences between the pre and post- SFAS 141 revision periods. Magnitudes and signs of the *BVE_adj*, *Abearnings*, and *Accruals* coefficients are similar to those in prior research using the Ohlson (1999) valuation framework (Barth et al. 1999).[22]

[22] In particular, consistent with prior research, we find statistically significant coefficients with correct signs in all our autoregressive processes (Barth et al. 1999).

Table 2 Panel A: Valuation equation of definite and indefinite intangible assets

Table 2 Panel A reports estimated coefficients including our variables of interest: definite (*Def_int*) and indefinite (*Indef_int*) intangible assets (equation 1(f) of *System 1*). Columns 1 and 2 present coefficients from unconstrained and constrained estimations over the entire sample period (2003-2018). Constrained estimators are derived and presented in Appendix C. Column 3a and 3b present coefficients from constrained estimations for the pre- and post-SFAS 141R revision periods, 2003-2008 and 2009-2018. Coefficients for column 3a and 3b are estimated using a fully interacted model that uses indicator variables for the pre- and post- SFAS 141R revision periods. Column 3c presents differences between pre- and post-SFAS 141R-coefficients. Two-tailed p-values are reported in parentheses below each coefficient for the null of zero. ***, **,* indicate 1%, 5%, and 10% significance levels of Wald tests for differences between *Def_int* and *Indef_int* coefficients. All regressions include year indicator variables (Time FE) and Fama-French 49 industry indicator variables (Industry FE). R-Squared represents the fit of the valuation equation based on the seemingly unrelated regression (SUR) – estimator. F-Test presents the Chi²-test statistic for the sum of *Def_int* and *Indef_int* being equal to 0. We scale all variables by shares outstanding. Table 2 Panel B reports estimated coefficients of the change in persistence parameters between pre- and post-SFAS 141R period. We report both pre- and post-SFAS 141R persistence parameters for *Def_int* and *Indef_Int*. We test the difference with a Wald Test. Two-tailed p-values are reported in parentheses below each coefficient for the null of zero.

		1	***2***	***3a***	***3b***	***3c***
		Unconstrained estimation	***Constrained estimation***	***Constrained estimation***		
		complete sample (2003-2018)	***complete sample (2003-2018)***	***pre-SFAS R (2003-2008)***	***post-SFAS R (2009-2018)***	***Difference pre- and post-SFAS R***
VARIABLES	***Prediction***	*MVE*	*MVE*	*MVE*	*MVE*	
BVE_adj	+	1.287	1.277	1.127	1.329	0.202
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Abearnings	+	6.946	7.080	5.053	7.526	2.473
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Accruals	-	-3.109	-3.355	-1.922	-3.492	-1.570
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Def_Int	+	2.538***	2.537***	3.326***	3.174***	-0.152
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Indef_Int	+	0.864***	0.403***	0.652***	0.604***	-0.048
		(0.000)	(0.000)	(0.000)	(0.000)	(0.003)
Time FE		YES	YES	YES	YES	
Industry FE		YES	YES	YES	YES	
R-Squared		0.569	0.566	0.582		
F-Test		1728.20 (0.000)	1257.17 (0.000)	1423.34 (0.000)	1382.05 (0.000)	
Observations		16,508	16,508	16,508	16,508	

Table 2 Panel B: Change in persistence parameter tests between pre- and post-SFAS 141R period

	Def_int (ω_{44})	*Indef_int*(ω_{55})
Pre coefficient (System 1)	1.059	0.947
Post Coefficient (System 1)	0.977	0.937
Difference Pre – Post	-0.082	-0.010
Wald Test Difference	65.69	1.74
p-value Difference	(0.000)	(0.187)

Regarding our first research question, the findings in Columns 1 and 2 reveal that the coefficients for definite intangible assets, *Def_Int*, 2.538 and 2.537, are positive and significantly different from zero.[23] Findings in Columns 3a through 3c reveal that the *Def_Int* coefficient is significantly larger in the pre-period by 0.152. This result indicates that the revision of SFAS 141 in 2008 altered valuation implications for definite intangibles, and suggests that investors use more precise disclosures about valuation models and valuation inputs to revise cash flow expectations (risk assessment) of definite intangibles downward (upward), which leads to lower coefficients. To identify the prevalent channel regarding the downward revision in coefficients, we propose a test of the persistence parameters for each intangible asset in our generalized Ohlson (1999) framework. In particular, we test autoregressive parameters of *Def_Int* of pre- against post- SFAS 141 revision periods to investigate changes in persistence. Table 2, Panel B, reports coefficients for pre- and post-SFAS 141R autoregressive parameters with Wald tests for their difference. For *Def_Int*, we find a significant downward revision in persistence. This result is consistent with the revision of coefficients of definite intangibles are attributable to investors revising downward cash flow expectations and potentially increasing their risk assessment of definite intangibles.

The findings in Columns 1 and 2 reveal that the coefficients for indefinite intangible assets, *Indef_Int*, 0.864 and 0.403, also are positive and significantly different from zero. The noticeably smaller valuation coefficient based on the constrained estimation yields more sensible estimates when we specify each intangible asset coefficient as a function of its relation to abnormal earnings and its own time-series properties. Indefinite intangible asset coefficients are, as expected, smaller and significantly so than those for definite intangibles. That is, investors regard definite intangible asset valuations as more precise than those for indefinite

[23] Throughout we use a five percent significance level under a one-sided alternative when we have a signed prediction and under a two-sided alternative otherwise.

intangibles. Taken together, the findings in Columns 1 and 2 indicate that we can reject hypothesis 1a that definite and indefinite intangible assets are valuation irrelevant.

The findings in Columns 3a-3c also reveal a significant decline in the indefinite intangible coefficients after the revision of SFAS 141. In particular, the *Indef_Int* coefficient is significantly smaller in the post-SFAS 141R period by 0.048. The coefficients in Table 2, Panel B, further indicate no significant change in persistence, which is consistent with investors not revising downward expected cash flows in the post-period. Thus, our results suggest that increased disclosure in the post-SFAS 141R period led investors to increase their risk assessments of indefinite intangible assets, which resulted in lower valuation coefficients. Therefore, we can reject hypothesis 1b that the valuation relevance of indefinite intangible assets did not change in the post-SFAS 141R period.

5.2 Tech-, customer-, contract-, and marketing intangibles

Next, we present findings regarding the value relevance for different intangible asset classes, tech-, customer-, contract-, and marketing intangibles. Table 3, Panel A, presents findings for *System 2*, with the same column structure as in Table 2, Panel A. Regarding our variables of interest, we find significantly positive coefficients for *all* intangible asset classes. For tech intangibles, the unconstrained and constrained coefficients are 4.647 and 4.628. These findings are consistent with prior research on internally generated R&D and purchased innovation in business combinations showing that tech intangibles are highly relevant in equity pricing (Lev and Sougiannis 1996; Hall et al. 2005; Bena and Li 2014). Although prior research findings suggest that tech fair values measured at acquisition date do not seem to predict future payoffs (McInnis and Monsen 2021), our findings suggest that comprehensively measured *net amounts* of acquired tech intangibles are value relevant for equity investors.

Table 3 Panel A: Valuation equation disaggregated into tech-, customer-, contract-, and marketing intangibles

Table 3 Panel A reports estimated coefficients including our variables of interest: tech- (*Tech*), customer- (*Customer*), contract- (*Contract*), and marketing-related (*Marketing*) intangible assets (equation 2(i) of *System 2*). Columns 1 and 2 present coefficients from unconstrained and constrained estimations over the entire sample period (2003-2018). Constrained estimators are derived and presented in Appendix C. Column 3a and 3b present coefficients from constrained estimations for the pre- and post-SFAS 141R revision periods, 2003-2008 and 2009-2018. Coefficients for column 3a and 3b are estimated using a fully interacted model that uses indicator variables for the pre- and post-SFAS 141R revision periods. Column 3c presents differences between pre- and post SFAS 141R-coefficients. Two-tailed p-values are reported in parentheses below each coefficient for the null of zero. All regressions include year indicator variables (Time FE) and Fama-French 49 industry indicator variables (Industry FE). R-Squared represents the fit of the valuation equation based on the seemingly unrelated regression (SUR) – estimator. F-Test presents the Chi²-test statistic for the sum of *Tech, Customer, Contract,* and *Marketing* being equal to 0. We scale all variables by shares outstanding. Table 3 Panel B reports estimated coefficients of the change in persistence parameters between pre- and post-SFAS 141R period. We report both pre- and post-SFAS 141R persistence parameters for *Tech*, Customer, Contract, and *Marketing*. We test the difference with a Wald Test. Two-tailed p-values are reported in parentheses below each coefficient for the null of zero.

		1	***2***	***3a***	***3b***	***3c***
		Unconstrained Estimation	***Constrained estimation***	***Constrained estimation***		
		complete sample (2003-2018)	***complete sample (2003-2018)***	***pre-SFAS R (2003-2008)***	***post-SFAS R (2009-2018)***	***Difference pre- and post-SFAS R***
VARIABLES	***Prediction***	*MVE*	*MVE*	*MVE*	*MVE*	
BVE_adj	+	1.276	1.274	1.139	1.307	0.168
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Abearnings	+	6.920	7.016	4.953	7.568	2.615
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Accruals	-	-3.129	-3.369	-1.898	-3.589	-1.691
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tech	+	4.647	4.628	5.680	5.238	-0.442
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Customer	+	2.480	2.015	3.174	2.861	-0.313
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Contract	+	1.146	0.705	0.805	0.713	-0.092
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Marketing	+	1.370	1.235	1.410	1.320	-0.090
		(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
Other	+	5.234	1.115	6.563	6.240	-0.323
		(0.000)	(0.010)	(0.000)	(0.000)	(0.010)
Time FE		YES	YES	YES	YES	
Industry FE		YES	YES	YES	YES	
R-Squared		0.572	0.568	0.584		
F-Test		1795.52 (0.000)	1291.86 (0.000)	1260.75 (0.000)	1389.16 (0.000)	
Observations		16,508	16,508	16,508	16,508	

Table 3 Panel B: Change in persistence parameter tests between pre- and post-SFAS 141R period

	Tech(ω_{44})	*Customer(ω_{55})*	*Contract(ω_{66})*	*Marketing(ω_{77})*
Pre coefficient (System 2)	0.996	0.978	0.961	0.966
Post Coefficient (System 2)	1.008	0.985	0.997	1.003
Difference Pre – Post	0.012	0.007	0.036	0.037
Wald Test Difference	0.88	0.28	43.81	19.39
p-value Difference	(0.349)	(0.597)	(0.000)	(0.000)

The customer intangibles coefficients from the unconstrained and constrained estimations, 2.480 and 2.015, are significantly positive. These results are consistent with the findings in McInnis and Monsen (2021) and Bauman and Shaw (2018) showing that customer intangible amounts contain valuable information for future payoffs. The significantly positive coefficient for contract intangibles, 0.705, suggests they are value relevant for equity investors. This finding is consistent with the findings in Galasso et al. (2013) and Bonacchi et al. (2015), both of which focus on the importance of licenses and franchises in the pharmaceutical- and retail industry. We significantly extend these studies and find that contract intangibles are value relevant for a large sample of firms. Lastly, marketing intangibles are also positive and significantly priced across every column. Consistent with Kallapur and Kwan (2004), and McInnis and Monsen (2021), we find that net amounts of acquired marketing intangibles are value relevant. Marketing intangibles are even significant in all time specifications.

As with the Table 2 findings relating to aggregate definite and indefinite intangibles, the findings in Table 3, Panel A, reveal that each of the separate intangible coefficients is smaller in the post- SFAS 141R period. The declines and partially insignificant changes in each intangibles persistence parameters, reported in Panel B, suggest that investors used the additional disclosures to revise their risk assessment upwards.

Taken together, all four intangible asset classes are value relevant for equity pricing. Results suggest that equity investors value *net amounts* of all acquired intangible asset classes. Particularly, *Tech* such as patents and developed technologies are highly relevant consistent with the recent increase in tech mergers (Lin and Wang 2016). Therefore, we can reject hypothesis 2a for each intangible asset class. Regarding hypothesis 2b, our coefficients show that equity investors significantly revise their valuations downward for all intangible asset classes. Our persistence tests additionally suggest that investors use a higher disclosure level for an upward revision in risk assessment of each intangible asset class (tech, customer, contract, marketing).

5.3 Disaggregation of intangible assets in definite- and indefinite-life intangible assets

Table 4 presents findings in which we disaggregate our four intangible asset classes into definite and indefinite intangible assets.

Regarding our third set of predictions, we find consistent results for many of our formed predictions. For tech intangibles, we find positively significant coefficients for both definite (*Tech_Def*) and indefinite (*Tech_Indef*) life intangible assets. *Tech_Indef* is mostly comprised of in-process R&D, which is why *Tech_Indef* is only observable after the passage of SFAS141R. Before revising SFAS 141, in-process R&D was the only acquired intangible that was excluded from the mandate for recognition. Consistent with Deng and Lev (2006), our results suggest that in-process R&D is a highly relevant item in equity valuation and recognition on the statement of financial position provides useful information. Importantly, however, *Tech_indef* is much less relevant in the constrained estimation relative to the unconstrained estimation. While having a coefficient of 15.162 (p-value<0.001) within our unconstrained estimation, imposing a linear information structure reduces *Tech_indef* to a more sensible estimate of 2.839 (p-value<0.001). Unconstrained estimations do not take into account the time series properties of indefinite tech intangibles and their potential forecasting abilities for abnormal earnings and accruals. This result underscores why imposing a linear information model is crucial to determine value relevance for intangible assets.

Table 4 Panel A: Valuation equation disaggregated into economic lifetimes (definite and indefinite) per asset class (tech-, customer-, contract-, marketing intangibles)

Table 4 Panel A reports estimated coefficients including our variables of interest: definite tech- (*Tech_def*), indefinite tech- (*Tech_indef*), customer- (*Customer*), definite contract- (*Contract_def*), indefinite contract- (*Contract_indef*), definite marketing- (*Marketing_def*), and indefinite marketing-related (*Marketing_indef*) intangible assets (equation 3(l) of *System 3*). Columns 1 and 2 present coefficients from unconstrained and constrained estimations over the entire sample period (2003-2018). Constrained estimators are derived and presented in Appendix C. Column 3a and 3b present coefficients from constrained estimations for the pre- and post-SFAS 141R revision periods, 2003-2008 and 2009-2018. Coefficients for column 3a and 3b are estimated using a fully interacted model that uses indicator variables for the pre- and post-SFAS 141R revision periods. Column 3c presents differences between pre- and post SFAS 141R-coefficients. Two-tailed p-values are reported in parentheses below each coefficient for the null of zero. ***, **,* indicate 1%, 5%, and 10% significance levels of Wald tests for differences between *Tech_Def* and *Tech_Indef, Contract_Def* and *Contract_Indef,* and *Marketing_Def* and *Marketing_Indef* coefficients. All regressions include year indicator variables (Time FE) and Fama-French 49 industry indicator variables (Industry FE). R-Squared represents the fit of the valuation equation based on the seemingly unrelated regression (SUR) – estimator. F-Test presents the Chi²-test statistic for the sum of our variables of interests being equal to 0. We scale all variables by shares outstanding. Table 4 Panel B reports estimated coefficients of the change in persistence parameters between pre- and post-SFAS 141R period. We report both pre- and post-SFAS 141R persistence parameters for *Tech_Def*, *Customer*, *Contract_Def*, *Contract_Indef* , *Marketing_Def* and *Marketing_Indef*. We test the difference with a Wald Test. Two-tailed p-values are reported in parentheses below each coefficient for the null of zero. Wald Test of the sum presents the Chi²-test statistic for the sum of definite and indefinite intangible assets being equal to 0.

		1	***2***	***3a***	***3b***	***3c***
		Unconstrained estimation	***Constrained estimation***	***Constrained estimation***		
		complete sample (2003-2018)	***complete sample (2003-2018)***	***pre-SFAS R (2003-2008)***	***post-SFAS R (2009-2018)***	***Difference pre- and post-SFAS R***
VARIABLES	***Prediction***	*MVE*	*MVE*	*MVE*	*MVE*	
BVE_adj	+	1.258	1.263	1.114	1.299	0.185
		(0.000)	(0.000)	(0.000)	(0.000)	(0.009)
Abearnings	+	8.642	7.050	4.961	7.548	2.587
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Accruals	-	-2.601	-3.475	-1.980	-3.641	-1.661
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tech_Def	+	3.748***	3.957	5.627	5.014	-0.613
		(0.000)	(0.000)	(0.000)	(0.000)	(0.010)
Tech_Indef	+	15.162***	2.839		5.711	
		(0.000)	(0.002)		(0.000)	
Customer	+	2.629	2.157	3.297	3.014	-0.283
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Contract_Def	+	3.023***	2.394***	3.165***	2.759***	-0.406
		(0.000)	(0.000)	(0.038)	(0.000)	(0.000)
Contract_Indef	+	0.874***	0.362***	0.662***	0.648***	-0.015
		(0.000)	(0.000)	(0.000)	(0.000)	(0.640)
Marketing_Def	+	2.530*	0.392	1.606	1.333	-0.273
		(0.001)	(0.565)	(0.061)	(0.085)	(0.114)
Marketing_Indef	+	1.253*	1.194	1.226	1.158	-0.069
		(0.000)	(0.000)	(0.000)	(0.000)	(0.023)
Other	+	5.083	4.709	6.626	6.272	-0.353
		(0.000)	(0.000)	(0.000)	(0.000)	(0.004)
Time FE		YES	YES	YES	YES	
Industry FE		YES	YES	YES	YES	
R-Squared		0.570	0.564	0.582		
F-Test		387.51 (0.000)	145.25 (0.000)	283.46 (0.000)	273.27 (0.000)	
Observations		16,508	16,508	16,508	16,508	

Table 4 Panel B: Change in persistence parameter tests between pre- and post-SFAS 141R period

	Tech_Def(ω_{44})	*Customer(ω_{55})*	*Contract_Def(ω_{66})*	*Contract_Indef(ω_{77})*	*Marketing_Def(ω_{88})*	*Marketing_Indef(ω_{99})*
Pre coefficient (System 3)	0.971	0.982	0.989	0.969	0.947	0.958
Post Coefficient (System 3)	0.978	0.981	0.970	0.958	0.958	1.013
Difference Pre – Post	0.007	-0.001	-0.019	-0.011	0.011	0.055
Wald Test Difference	0.47	0.01	4.03	3.40	1.33	37.46
p-value Difference	(0.493)	(0.910)	(0.045)	(0.065)	(0.248)	(0.000)

Wald Test of sum of persistence changes of definite intangibles (Tech_def, Customer, Contract_Def,Marketing_Def)	0.02 (0.900)
Wald Test of sum of persistence changes of indefinite intangibles (Contract_Indef, Marketing_Indef)	16.07 (0.000)

Regarding customer intangibles, we find results that yield similar inferences to those as in Table 3, Panel A. For contract intangibles, the findings reveal significantly positive coefficients for both definite and indefinite contract intangibles. The findings also reveal that definite contract are more relevant than indefinite contract intangibles, which is consistent with prior findings that aggregate definite intangibles are more relevant than aggregate indefinite intangibles. Lastly, we find positive and statistically significant coefficients for indefinite marketing intangibles. For definite marketing intangibles, however, we find mixed results. This can be attributable to that fact that definite marketing intangibles contain several intangibles such as definite trademarks and non-compete agreements (*NCA*) that provide low economic benefits and due to low enforcement and not be in use. We test for value relevance of *NCA*s separately within our fourth system below. Taken together, the Table 4 findings lead us to reject hypothesis 3a for most intangible assets investigated.

Consistent with the findings in Table 2 and 3, the findings in Table 4, Panel A, reveal significant decreases in valuation coefficients regardless of intangible class or economic lifetime, except for *Contract_indef* and *Marketing_def*. Persistence tests, reported in Panel B, again suggest that the lower valuation coefficients in the post-period is attributable to investors' higher risk assessments rather than downward revisions in cash flow expectations. Therefore, we can reject hypothesis 3b.

5.4 Evaluation of FASB proposal

Table 5 presents findings from estimations of *System 4*, which separates definite marketing intangibles from non-compete agreements (*NCA*). The findings reveal an economically and statistically significant coefficient for customer intangibles, which confirms our results from our two prior tests (see also Dikolli et al. 2007; Bauman and Shaw 2018; McInnis and Monsen 2021). More importantly, we find no significant coefficients for *NCAs* across all specifications. These results are consistent with several claims of valuation experts and preparers that the capitalization of acquired non-compete agreements provides no decision relevant information for equity investors. Therefore, we can reject hypothesis 4 with regard to *Customer*, but not for *NCA*s. Taken together, the results across all our specifications suggest that customer intangibles should not be subsumed into goodwill because they carry decision useful information.

Table 5: Valuation equation of customer intangibles and non-compete agreements

Table 5 reports estimated coefficients including our variables of interest: customer-related intangible assets (*Customer*) and non-compete agreements (*NCA*) (equation 4(m) of *System 4*). Columns 1 and 2 present coefficients from unconstrained and constrained estimations over the entire sample period (2003-2018). Constrained estimators are derived and presented in Appendix C. Column 3a and 3b present coefficients from constrained estimations for the pre- and post-SFAS 141R revision periods, 2003-2008 and 2009-2018. Coefficients for column 3a and 3b are estimated using a fully interacted model that uses indicator variables for the pre- and post-SFAS 141R revision periods. Column 3c presents differences between pre- and post-SFAS 141R-coefficients. Two-tailed p-values are reported in parentheses below each coefficient for the null of zero. ***, **,* indicate 1%, 5%, and 10% significance levels of Wald tests for differences between *Tech_Def* and *Tech_Indef*, *Contract_Def* and *Contract_Indef*, and *Marketing_Def_ex* and *Marketing_Indef* coefficients. All regressions include year indicator variables (Time FE) and Fama-French 49 industry indicator variables (Industry FE). R-Squared represents the fit of the valuation equation based on the seemingly unrelated regression (SUR) – estimator. F-Test presents the Chi²-test statistic for the sum of our variables of interests being equal to 0. We scale all variables by shares outstanding.

		1	***2***	***3a***	***3b***	***3c***
		Unconstrained estimation	***Constrained estimation***	***Constrained estimation***		
		complete sample (2003-2018)	***complete sample (2003-2018)***	***pre-SFAS R (2003-2008)***	***post-SFAS R (2009-2018)***	***Difference pre- and post-SFAS R***
VARIABLES	***Prediction***	*MVE*	*MVE*	*MVE*	*MVE*	
BVE_adj	+	1.259	1.263	1.115	1.299	0.184
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Abearnings	+	6.925	7.048	4.995	7.584	2.589
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Accruals	-	-3.199	-3.473	-1.975	-3.639	-1.664
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tech_Def	+	3.749***	3.874	5.610	4.996	-0.614
		(0.000)	(0.000)	(0.000)	(0.000)	(0.010)
Tech_Indef	+	15.160***	3.107		5.722	
		(0.000)	(0.001)		(0.000)	
Customer	+	2.648	2.160	3.305	3.033	-0.273
		(0.000)	(0.000)	(0.000)	(0.000)	(0.635)
Contract_Def	+	3.045***	2.402***	3.186***	2.782***	-0.404
		(0.000)	(0.000)	(0.030)	(0.000)	(0.000)
Contract_Indef	+	0.876***	0.370***	0.666***	0.651***	-0.015
		(0.000)	(0.003)	(0.000)	(0.000)	(0.615)
Marketing_Def_ex	+	2.507	0.921	2.162	1.866	-0.296
		(0.001)	(0.198)	(0.015)	(0.022)	(0.078)
NCA	+	-4.154	-10.530	-12.082	-11.676	0.406
		(0.675)	(0.103)	(0.199)	(0.151)	(0.857)
Marketing_Indef	+	1.247	1.184	1.221	1.151	-0.071
		(0.000)	(0.000)	(0.000)	(0.000)	(0.021)
Other	+	5.072	4.647	6.573	6.218	-0.355
		(0.000)	(0.000)	(0.000)	(0.000)	(0.004)
Time FE		YES	YES	YES	YES	
Industry FE		YES	YES	YES	YES	
R-Squared		0.571	0.567	0.582		
F-Test		387.74	155.56	281.91	274.63	
		(0.000)	(0.000)	(0.000)	(0.000)	
Observations		16,508	16,508	16,508	16,508	

5.5 Additional tests

We validate our findings through three additional tests, with findings presented in the online Appendix B. First, we estimate each system using operating cash flows instead of accruals (Barth et al. 1999). Results, presented in Appendix B, Table B1-B4, yield the same inferences as those based on the accruals-based system. Second, we re-estimate our tests using two different discount rates for abnormal earnings, eight and ten percent. Untabulated results yield the same inferences as those on the twelve percent discount rate. Third, we follow Barth et al. (1999) and estimate our equation system on an industry level. We do this because Sandner and Block (2011), among others, suggests that valuation implications may differ between industries. In particular, we re-estimate our research design on an industry level using the Fama-French-12 industry classification including year fixed effects (Fama and French 1997, Barth et al. 1999). Table 6 presents findings within industry estimations, wherein for the sake of parsimony we only include definite and indefinite intangible assets. Coefficients reveal mostly the same inferences as those based on the tabulated findings in which we pool observations across industries using industry fixed effects. Notably for definite intangible assets (indefinite intangibles), the findings reveal significantly positive coefficients in eleven (ten) out of twelve industries, and coefficients for *Def_int* are higher than *Indef_int* in eight industries confirming our prior results from Table 2.

Table 6: Industry regression for definite and indefinite intangible assets

Table 6 reports estimated coefficients by industry including our variables of interest: definite (*Def_int*) and indefinite (*Indef_int*) intangible assets (equation 1(f) of *System 1*). We define industries using Fama-French 12 industry classification. Both constrained and unconstrained coefficients are estimated over the entire sample period (2003-2018). An example of a constrained estimator is derived and presented in Appendix C. Bold numbers indicate significant coefficients on the ten percent level or better. Two-tailed p-values are reported in parentheses below each coefficient significantly different from zero. All regressions include year indicator variables (*Time FE*). We scale all variables by shares outstanding.

	estimation	*BVE_adj*	*Def_Int*	*Indef_Int*	*Abearnings*	*Accruals*	*N*
Nondurables	***constrained coeff.***	**1.133**	**0.729**	**0.991**	**6.341**	**-2.557**	*1651*
	P-values	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	
	unconstrained coeff.	***1.134***	***0.902***	***1.129***	***6.052***	***-2.173***	
	P-values	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	
Durables	***constrained coeff.***	**1.468**	**2.070**	**0.469**	**3.107**	**-3.816**	*696*
	P-values	*0.000*	*0.000*	*0.092*	*0.000*	*0.000*	
	unconstrained coeff.	**1.394**	**2.931**	**1.263**	**2.735**	**-3.132**	
	P-values	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	
Manufacturing	***constrained coeff.***	**1.231**	**2.380**	**2.002**	**10.209**	**-4.830**	*1544*
	P-values	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	
	unconstrained coeff.	**1.204**	**2.647**	**2.112**	**10.136**	**-4.747**	
	P-values	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	
Oil&Gas	***constrained coeff.***	**1.030**	**5.085**	**6.881**	**2.459**	**-1.797**	*806*
	P-values	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	
	unconstrained coeff.	**1.030**	**3.602**	5.045	**2.466**	**-1.796**	
	P-values	*0.000*	*0.000*	*0.145*	*0.000*	*0.000*	
Chemicals	***constrained coeff.***	**1.224**	**0.997**	**3.141**	**11.909**	**-6.529**	*816*
	P-values	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	
	unconstrained coeff.	**1.260**	**1.626**	**3.592**	**11.895**	**-6.383**	
	P-values	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	
Business & Equipment	***constrained coeff.***	**1.379**	**2.555**	-0.049	**9.149**	**-4.549**	*2908*
	P-values	*0.000*	*0.000*	*0.949*	*0.000*	*0.000*	
	unconstrained coeff.	**1.299**	**3.033**	1.120	**9.140**	**-4.352**	
	P-values	*0.000*	*0.000*	*0.249*	*0.000*	*0.000*	
Telephone & Television	***constrained coeff.***	**0.648**	**1.527**	**0.688**	**3.616**	**-1.644**	*821*
	P-values	*0.000*	*0.000*	*0.000*	*0.000*	*0.006*	
	unconstrained coeff.	**0.732**	**1.531**	**0.953**	**3.255**	**-1.165**	
	P-values	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	
Utilities	***constrained coeff.***	**1.022**	0.367	1.204	**5.514**	**-2.489**	*621*
	P-values	*0.000*	*0.363*	*0.415*	*0.000*	*0.000*	
	unconstrained coeff.	**1.027**	**0.944**	-0.632	**5.449**	**-2.447**	
	P-values	*0.000*	*0.021*	*0.864*	*0.000*	*0.000*	
Shops	***constrained coeff.***	**1.161**	**1.633**	**0.450**	**12.139**	**-7.089**	*2108*
	P-values	*0.000*	*0.000*	*0.040*	*0.000*	*0.000*	
	unconstrained coeff.	**1.147**	**2.071**	**0.790**	**12.167**	**-6.285**	
	P-values	*0.000*	*0.000*	*0.001*	*0.000*	*0.000*	
Health	***constrained coeff.***	**1.977**	**2.736**	**1.382**	**4.951**	**-4.369**	*2007*
	P-values	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	
	unconstrained coeff.	**1.987**	**1.983**	**2.585**	**4.833**	**-4.057**	
	P-values	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	
Finance	***constrained coeff.***	**1.287**	**4.566**	**1.258**	**4.706**	**-0.876**	*719*
	P-values	*0.000*	*0.000*	*0.000*	*0.000*	*0.001*	
	unconstrained coeff.	**1.287**	**3.499**	**1.153**	**4.672**	**-0.881**	
	P-values	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	
Other	***constrained coeff.***	**1.232**	**6.129**	**1.696**	**6.200**	**-1.734**	*1811*
	P-values	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	
	unconstrained coeff.	**1.243**	**5.464**	**2.183**	**6.175**	**-1.622**	
	P-values	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	

6. Summary and concluding remarks

This study examines the value relevance of acquired intangible assets in equity valuation. In particular, we investigate value relevance of different specifications of acquired intangible assets on stock prices. We base our analysis on an adjusted Ohlson (1999) valuation framework in line with Barth et al. (1999; 2005). We predict and find that net amounts of acquired intangibles are positively priced in equity markets. First, we find that both definite and indefinite intangible assets are positively associated with stock prices demonstrating a high relevance for equity investors. Second, we investigate four different intangible asset classes: tech-, customer-, contract-, and marketing intangibles. Other categories such as customer-, contract-, and marketing intangibles are also value relevant, yet, not as economically relevant as tech intangibles. Third, we disaggregate our four intangible asset classes into definite and indefinite intangible assets and find positive associations for definite and indefinite intangibles. Fourth, our empirical findings speak against the recent FASB proposal for subsuming customer intangibles and non-compete agreements into goodwill. While we find no associations between non-compete agreements and stock prices, we find significantly positive coefficients for customer-related intangibles. Our results imply that subsuming customer-related intangible assets into the goodwill would lead to a loss of relevant information for equity investors.

Overall, our study answers recent calls from both academics and standard setters (FASB and IASB) to investigate the usefulness of acquired intangible asset amounts. Our study is based on the most comprehensive dataset for acquired intangible asset classes tracking their post-acquisition values over time. Eventually, our paper directly speaks to potential losses in decision-relevant information for equity market participants when changing accounting for acquired intangible assets.

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Appendix to

"The pricing of acquired intangibles"

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Table of Contents

A. Variable definitions

Variable	Description	Data source
Dependent and independent variables:		
MVE	Market value of equity calculated with a three-month lag window.	CRSP
Abearnings	Abnormal earnings calculated as the difference between net income and normal earnings. Normal earnings are calculated with previous book value times the discount rate. We use a discount rate of 12 percent (Dechow et al. 1999; Barth et al. 1999).	Compustat
Accruals	Difference between net income to common shareholders and operating cash flows.	Compustat
CFO	Amount of cash flow from operating activities.	Compustat
BVE_adj	Book value of common equity subtracted by total amount of acquired intangible assets.	Compustat / Hand-collected
Intangible asset variables:		
Def_Int	Net amount of acquired definite intangible assets.	Hand-collected
Indef_Int	Net amount of acquired indefinite intangible assets.	Hand-collected
Tech	Net amount of definite and indefinite acquired tech-related intangible assets. This position includes mainly the following items: patents, developed technology, software, in-process R&D.	Hand-collected
Customer	Net amount of customer-related acquired intangible assets. This position includes mainly following items: Customer lists, customer relationships, customer contracts, order backlogs.	Hand-collected
Contract	Net amount of definite and indefinite purchased contract-related intangible assets. This position mainly includes the following items: licenses, contracts, agreements, land- and water rights, emission allowances, landing rights (for airline companies).	Hand-collected
Marketing	Net amount of definite and indefinite purchased marketing-related intangible assets. This position mainly includes the following items: trademarks and tradenames, domain names, mastheads, non-compete agreements.	Hand-collected
Other	Net amount of acquired intangible assets, which are not allocated into one of the four specific categories. For instance, it contains commingled positions as well as artistic intangible assets.	Hand-collected
Tech_Def	Net amount of acquired definite-lived tech-related intangible assets.	Hand-collected
Tech_Indef	Net amount of acquired indefinite-lived tech-related intangible assets. This category consist almost entirely of in-process R&D.	Hand-collected
Contract_Def	Net amount of acquired definite-lived contract-related intangible assets.	Hand-collected
Contract_Indef	Net amount of acquired indefinite-lived contract-related intangible assets. This category consists primarily of licenses and franchises.	Hand-collected
Marketing_Def	Net amount of acquired definite-lived marketing-related intangible assets.	Hand-collected
Marketing_Indef	Net amount of acquired indefinite-lived marketing-related intangible assets. This category is entirely comprised of trademarks.	Hand-collected
Marketing_Def_ex	Net amount of acquired definite-lived marketing-related intangible assets subtracted by acquired non-compete agreements.	Hand-collected
NCA	Net amount of acquired non-compete agreements.	Hand-collected

Table B1 Panel A: Valuation equation of definite and indefinite intangible assets

Table B1 Panel A reports estimated coefficients including our variables of interest: definite (*Def_int*) and indefinite (*Indef_int*) intangible assets (equation 1(f) of *System 1*). Columns 1 and 2 present coefficients from unconstrained and constrained estimations over the entire sample period (2003-2018). Constrained estimators are derived and presented in Appendix C. Column 3a and 3b present coefficients from constrained estimations for the pre- and post-SFAS 141R revision periods, 2003-2008 and 2009-2018. Column 3c presents differences between pre- and post-SFAS 141R-coefficients. Two-tailed p-values are reported in parentheses below each coefficient for the null of zero. ***, **,* indicate 1%, 5%, and 10% significance levels of Wald tests for differences between *Def_int* and *Indef_int* coefficients. All regressions include year indicator variables (Time FE) and Fama-French 49 industry indicator variables (Industry FE). R-Squared represents the fit of the valuation equation based on the seemingly unrelated regression (SUR) – estimator. F-Test presents the Chi²-test statistic for the sum of *Def_int* and *Indef_int* being equal to 0. We scale all variables by shares outstanding. Table 2 Panel B reports estimated coefficients of the change in persistence parameters between pre- and post-SFAS 141R period. We report both pre- and post-SFAS 141R persistence parameters for *Def_int* and *Indef_Int*. We test the difference with a Wald Test. Two-tailed p-values are reported in parentheses below each coefficient for the null of zero.

		1	***2***	***3a***	***3b***	***3c***
		Unconstrained estimation	***Constrained estimation***	***Constrained estimation***		
		complete sample (2003-2018)	***complete sample (2003-2018)***	***pre-SFAS R (2003-2008)***	***post-SFAS R (2009-2018)***	***Difference pre- and post-SFAS R***
VARIABLES	***Prediction***	*MVE*	*MVE*	*MVE*	*MVE*	
BVE_adj	+	0.893	0.855	0.844	0.895	0.051
		(0.000)	(0.000)	(0.000)	(0.000)	(0.265)
Abearnings	+	3.987	3.866	3.226	4.158	0.932
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CFO	+	3.409	3.701	2.279	3.833	1.554
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Def_Int	+	2.099***	2.200***	2.917***	2.740***	-0.177
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Indef_Int	+	0.292***	-0.048***	0.051***	0.033***	-0.018
		(0.000)	(0.443)	(0.537)	(0.659)	(0.285)
Time FE		YES	YES	YES	YES	
Industry FE		YES	YES	YES	YES	
R-Squared		0.587	0.584	0.599		
F-Test		769.20	527.37	642.17	581.78	
		(0.000)	(0.000)	(0.000)	(0.000)	
Observations		16,508	16,508	16,508	16,508	

Table B1 Panel B: Change in persistence parameter tests between pre- and post-SFAS 141R period

	Def_int (ω_{44})	*Indef_int*((ω_{55})
Pre coefficient (System 1)	1.041	0.935
Post Coefficient (System 1)	0,976	0.936
Difference Pre – Post	-0.065	0.001
Wald Test Difference	36.81	0.03
p-value Difference	(0.000)	(0.870)

Table B2 Panel A: Valuation equation disaggregated into tech-, customer-, contract-, and marketing intangibles

Table B2 Panel A reports estimated coefficients including our variables of interest: tech- (*Tech*), customer- (*Customer*), contract- (*Contract*), and marketing-related (*Marketing*) intangible assets (equation 2(i) of *System 2*). Columns 1 and 2 present coefficients from unconstrained and constrained estimations over the entire sample period (2003-2018). Constrained estimators are derived and presented in Appendix C. Column 3a and 3b present coefficients from constrained estimations for the pre- and post SFAS 141R revision periods, 2003-2008 and 2009-2018. Coefficients for column 3a and 3b are estimated using a fully interacted model that uses indicator variables for the pre- and post- SFAS 141R revision periods. Column 3c presents differences between pre- and post SFAS 141R-coefficients. Two-tailed p-values are reported in parentheses below each coefficient for the null of zero. All regressions include year indicator variables (Time FE) and Fama-French 49 industry indicator variables (Industry FE). R-Squared represents the fit of the valuation equation based on the seemingly unrelated regression (SUR) – estimator. F-Test presents the Chi²-test statistic for the sum of *Tech, Customer, Contract,* and *Marketing* being equal to 0. We scale all variables by shares outstanding. Table B2 Panel B reports estimated coefficients of the change in persistence parameters between pre and post-SFAS 141R period. We report both pre- and post-SFAS 141R persistence parameters for *Tech*, *Customer*, *Contract*, and *Marketing*. We test the difference with a Wald Test. Two-tailed p-values are reported in parentheses below each coefficient for the null of zero.

		1	***2***	***3a***	***3b***	***3c***
		Unconstrained estimation	***Constrained estimation***	***Constrained estimation***		
		complete sample (2003-2018)	***complete sample (2003-2018)***	***pre-SFAS R (2003-2008)***	***post-SFAS R (2009-2018)***	***Difference pre- and post-SFAS R***
VARIABLES	***Prediction***	*MVE*	*MVE*	*MVE*	*MVE*	
BVE_adj	+	0.887	0.849	0.851	0.875	0.024
		(0.000)	(0.000)	(0.000)	(0.000)	(0.650)
Abearnings	+	3.951	3.803	3.132	4.095	0.963
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CFO	+	3.389	3.704	2.261	3.423	1.162
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tech	+	4.031	4.431	5.290	4.825	-0.465
		(0.000)	(0.000)	(0.002)	(0.000)	(0.000)
Customer	+	2.015	1.628	2.717	2.363	-0.355
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Contract	+	0.557	0.125	0.192	0.100	-0.091
		(0.000)	(0.198)	(0.080)	(0.316)	(0.000)
Marketing	+	0.786	0.669	0.744	0.674	-0.070
		(0.000)	(0.000)	(0.000)	(0.000)	(0.012)
Other	+	4.156	0.461	5.697	5.474	-0.223
		(0.000)	(0.414)	(0.000)	(0.000)	(0.059)
Time FE		YES	YES	YES	YES	
Industry FE		YES	YES	YES	YES	
R-Squared		0.589	0.585	0.600		
F-Test		990.04	646.32	770.17	693.20	
		(0.000)	(0.000)	(0.000)	(0.000)	
Observations		16,508	16,508	16,508	16,508	

Table B2 Panel B: Change in persistence parameter tests between pre- and post-SFAS 141R period

	Tech(ω_{44})	*Customer(ω_{55})*	*Contract(ω_{66})*	*Marketing(ω_{77})*
Pre coefficient (System 2)	0.979	0.969	0.958	0.958
Post Coefficient (System 2)	1.008	0.984	0.998	1.003
Difference Pre – Post	0.029	0.015	0.040	0.045
Wald Test Difference	6.12	1.22	50.95	27.61
p-value Difference	(0.013)	(0.269)	(0.000)	(0.000)

Table B3 Panel A: Valuation equation disaggregated into economic lifetimes (definite and indefinite) per asset class (tech-, customer-, contract-, marketing intangibles)

Table B3 Panel A reports estimated coefficients including our variables of interest: definite tech- (*Tech_def*), indefinite tech- (*Tech_indef*), customer- (*Customer*), definite contract- (*Contract_def*), indefinite contract- (*Contract_indef*), definite marketing- (*Marketing_def*), and indefinite marketing-related (*Marketing_indef*) intangible assets (equation 3(l) of *System 3*). Columns 1 and 2 present coefficients from unconstrained and constrained estimations over the entire sample period (2003-2018). Constrained estimators are derived and presented in Appendix C. Column 3a and 3b present coefficients from constrained estimations for the pre- and post-SFAS 141R revision periods, 2003-2008 and 2009-2018. Coefficients for column 3a and 3b are estimated using a fully interacted model that uses indicator variables for the pre- and post-SFAS 141R revision periods. Column 3c presents differences between pre- and post-SFAS 141R-coefficients. Two-tailed p-values are reported in parentheses below each coefficient for the null of zero. ***, **,* indicate 1%, 5%, and 10% significance levels of Wald tests for differences between *Tech_Def* and *Tech_Indef, Contract_Def* and *Contract_Indef,* and *Marketing_Def* and *Marketing_Indef* coefficients. All regressions include year indicator variables (Time FE) and Fama-French 49 industry indicator variables (Industry FE). R-Squared represents the fit of the valuation equation based on the seemingly unrelated regression (SUR) – estimator. F-Test presents the Chi²-test statistic for the sum of our variables of interests being equal to 0. We scale all variables by shares outstanding. Table B3 Panel B reports estimated coefficients of the change in persistence parameters between pre- and post-SFAS 141R period. We report both pre- and post-SFAS 141R persistence parameters for *Tech_Def*, *Customer*, *Contract_Def, Contract_Indef* , *Marketing_Def* and *Marketing_Indef*. We test the difference with a Wald Test. Two-tailed p-values are reported in parentheses below each coefficient for the null of zero. Wald Test of the sum presents the Chi²-test statistic for the sum of definite and indefinite intangible assets being equal to 0.

		1	***2***	***3a***	***3b***	***3c***
		Unconstrained estimation	***Constrained estimation***	***Constrained estimation***		
VARIABLES	***Prediction***	***complete sample (2003-2018)*** *MVE*	***complete sample (2003-2018)*** *MVE*	***pre-SFAS R (2003-2008)*** *MVE*	***post-SFAS R (2009-2018)*** *MVE*	***Difference pre- and post-SFAS R***
BVE_adj	+	0.863	0.829	0.827	0.860	0.033
		(0.000)	(0.000)	(0.000)	(0.000)	(0.501)
Abearnings	+	3.899	3.751	3.115	4.063	0.948
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CFO	+	3.472	3.814	2.332	2.922	1.605
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tech_Def	+	3.202***	3.602	5.233	4.656	-0.577
		(0.000)	(0.000)	(0.017)	(0.000)	(0.000)
Tech_Indef	+	13.333***	2.464		4.860	
		(0.000)	(0.009)		(0.000)	
Customer	+	2.153	1.758	2.822	2.494	-0.328
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Contract_Def	+	2.053***	1.468***	2.299***	1.928***	-0.372
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Contract_Indef	+	0.105***	-0.288***	-0.228***	-0.218***	0.010
		(0.434)	(0.029)	(0.183)	(0.580)	(0.741)
Marketing_Def	+	1.420	-0.548	0.725	0.506	-0.218
		(0.047)	(0.447)	(0.426)	(0.538)	(0.193)
Marketing_Indef	+	0.632	0.584	0.527	0.494	-0.032
		(0.000)	(0.000)	(0.000)	(0.000)	(0.277)
Other	+	4.046	4.151	5.785	5.537	-0.248
		(0.000)	(0.000)	(0.000)	(0.000)	(0.037)
Time FE		YES	YES	YES	YES	
Industry FE		YES	YES	YES	YES	
R-Squared		0.588	0.583	0.599		
F-Test		242.70 (0.000)	61.69 (0.000)	131.12 (0.000)	133.48 (0.000)	
Observations		16,508	16,508	16,508	16,508	

Table B3 Panel B: Change in persistence parameter tests between pre- and post-SFAS 141R period

	Tech_Def(ω_{44})	*Customer(ω_{55})*	*Contract_Def(ω_{66})*	*Contract_Indef(ω_{77})*	*Marketing_Def(ω_{88})*	*Marketing_Indef(ω_{99})*
Pre coefficient (System 3)	0.963	0.970	0.986	0.967	0.945	0.949
Post Coefficient (System 3)	0.977	0.980	0.969	0.959	0.958	1.013
Difference Pre – Post	0.014	0.010	-0.017	-0.008	0.013	0.064
Wald Test Difference	1.91	0.58	3.24	1.83	2.02	47.94
p-value Difference	(0.167)	(0.447)	(0.072)	(0.177)	(0.155)	(0.000)

Wald Test of sum of persistence changes of definite intangibles (Tech_def, Customer, Contract_Def,Marketing_Def)	0.87 (0.351)
Wald Test of sum of persistence changes of indefinite intangibles (Contract_Indef, Marketing_Indef)	24.95 (0.000)

Table B4: Valuation equation of customer intangibles and non-compete agreements

Table B4 reports estimated coefficients including our variables of interest: customer-related intangible assets (*Customer*) and non-compete agreements (*NCA*) (equation 4(m) of *System 4*). Columns 1 and 2 present coefficients from unconstrained and constrained estimations over the entire sample period (2003-2018). Constrained estimators are derived and presented in Appendix C. Column 3a and 3b present coefficients from constrained estimations for the pre- and post-SFAS 141R revision periods, 2003-2008 and 2009-2018. Coefficients for column 3a and 3b are estimated using a fully interacted model that uses indicator variables for the pre- and post-SFAS 141R revision periods. Column 3c presents differences between pre- and post-SFAS 141R-coefficients. Two-tailed p-values are reported in parentheses below each coefficient for the null of zero. ***, **,* indicate 1%, 5%, and 10% significance levels of Wald tests for differences between *Tech_Def* and *Tech_Indef, Contract_Def* and *Contract_Indef,* and *Marketing_Def_ex* and *Marketing_Indef* coefficients. All regressions include year indicator variables (Time FE) and Fama-French 49 industry indicator variables (Industry FE). R-Squared represents the fit of the valuation equation based on the seemingly unrelated regression (SUR) – estimator. F-Test presents the Chi²-test statistic for the sum of our variables of interests being equal to 0. We scale all variables by shares outstanding.

		1	***2***	***3a***	***3b***	***3c***
		Unconstrained estimation	***Constrained estimation***	***Constrained estimation***		
		complete sample (2003-2018)	***complete sample (2003-2018)***	***pre-SFAS R (2003-2008)***	***post-SFAS R (2009-2018)***	***Difference pre- and post-SFAS R***
VARIABLES	***Prediction***	*MVE*	*MVE*	*MVE*	*MVE*	
BVE_adj	+	0.864	0.830	0.829	0.861	0.032
		(0.000)	(0.000)	(0.000)	(0.000)	(0.484)
Abearnings	+	3.898	3.751	3.114	4.063	0.949
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cash Flow	+	3.473	3.814	2.328	3.936	1.608
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tech_Def	+	3.198***	3.709*	5.205	4.628	-0.577
		(0.000)	(0.000)	(0.017)	(0.000)	(0.000)
Tech_Indef	+	13.329***	1.744*		4.860	
		(0.000)	(0.072)		(0.000)	
Customer	+	2.172	1.732	2.833	2.518	-0.316
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Contract_Def	+	2.073***	1.488***	2.315	1.947	-0.368
		(0.000)	(0.000)	(0.073)	(0.000)	(0.000)
Contract_Indef	+	0.108***	-0.285***	-0.224	-0.214	0.010
		(0.424)	(0.031)	(0.191)	(0.175)	(0.751)
Marketing_Def_ex	+	1.521	0.789	1.433	1.214	-0.220
		(0.036)	(0.918)	(0.130)	(0.164)	(0.177)
NCA	+	-8.493	-14.281	-15.343	-15.292	0.051
		(0.382)	(0.030)	(0.120)	(0.356)	(0.982)
Marketing_Indef	+	0.623	0.570	0.519	0.485	-0.034
		(0.000)	(0.000)	(0.001)	(0.000)	(0.263)
Other	+	4.023	4.115	5.715	5.467	-0.248
		(0.000)	(0.000)	(0.000)	(0.000)	(0.037)
Time FE		YES	YES	YES	YES	
Industry FE		YES	YES	YES	YES	
R-Squared		0.588	0.582	0.599		
F-Test		242.73 (0.000)	56.60 (0.000)	(0.000)	(0.000)	
Observations		16,508	16,508	16,508	16,508	

Table B5: Industry regressions for definite and indefinite intangible assets (cash flow design)

Table B5 reports estimated coefficients on industry level including our variables of interest: definite (Def_int) and indefinite (Indef_int) intangible assets (equation 1f of our *System 1*, substituting cash flows for accruals). We define industries using Fama-French 12 industry classification. Both constrained and unconstrained coefficients are estimated over the entire sample period (2003-2018). An example of a constrained estimator is derived and presented in Appendix C. Bold numbers indicate significant coefficients on the ten percent level. Two-tailed p-values are reported in parentheses below each coefficient significantly different from zero. All regressions include year indicator variables (Time FE). We scale all variables by shares outstanding.

	estimation	*BVE_adj*	*Def_Int*	*Indef_Int*	*Abearnings*	*CFO*	*N*
Nondurables	***constrained coeff.***	**0.846**	**0.492**	**0.661**	**4.109**	**2.478**	*1651*
	P-values	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	
	unconstrained coeff.	**0.907**	**0.729**	**0.775**	**4.225**	**2.022**	
	P-values	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	
Durables	***constrained coeff.***	**0.924**	**1.870**	0.006	-0.508	**4.270**	*696*
	P-values	*0.000*	*0.000*	*0.984*	*0.212*	*0.000*	
	unconstrained coeff.	**0.965**	**2.570**	**0.735**	-0.245	**3.467**	
	P-values	*0.000*	*0.000*	*0.018*	*0.552*	*0.000*	
Manufacturing	***constrained coeff.***	**0.676**	**2.218**	**1.734**	**5.810**	**4.935**	*1544*
	P-values	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	
	unconstrained coeff.	**0.668**	**2.045**	**1.512**	**5.843**	**4.767**	
	P-values	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	
Oil&Gas	***constrained coeff.***	**0.810**	**5.148**	6.441	**0.708**	**1.921**	*806*
	P-values	*0.000*	*0.000*	*0.155*	*0.000*	*0.000*	
	unconstrained coeff.	**0.810**	**3.426**	4.252	**0.719**	**1.919**	
	P-values	*0.000*	*0.000*	*0.215*	*0.000*	*0.000*	
Chemicals	***constrained coeff.***	**0.371**	0.460	**3.269**	**4.301**	**6.640**	*816*
	P-values	*0.000*	*0.164*	*0.000*	*0.000*	*0.000*	
	unconstrained coeff.	**0.428**	**0.859**	**2.822**	**4.489**	**6.448**	
	P-values	*0.000*	*0.002*	*0.000*	*0.000*	*0.000*	
Business & Equipment	***constrained coeff.***	**0.717**	**2.386**	**-1.507**	**4.873**	**5.756**	*2908*
	P-values	*0.000*	*0.000*	*0.082*	*0.000*	*0.000*	
	unconstrained coeff.	**0.688**	**2.424**	-0.462	**5.128**	**5.377**	
	P-values	*0.000*	*0.000*	*0.626*	*0.000*	*0.000*	
Telephone & Television	***constrained coeff.***	**0.439**	**1.323**	**0.377**	**2.062**	**1.780**	*821*
	P-values	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	
	unconstrained coeff.	**0.580**	**1.308**	**0.734**	**2.180**	**1.280**	
	P-values	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	
Utilities	***constrained coeff.***	**0.686**	0.147	1.868	**3.062**	**2.800**	*621*
	P-values	*0.000*	*0.723*	*0.218*	*0.000*	*0.000*	
	unconstrained coeff.	**0.693**	**0.671**	-1.115	**3.052**	**2.762**	
	P-values	*0.000*	*0.097*	*0.760*	*0.000*	*0.000*	
Shops	***constrained coeff.***	**0.556**	**0.678**	-0.274	**5.943**	**6.227**	*2108*
	P-values	*0.000*	*0.026*	*0.250*	*0.000*	*0.000*	
	unconstrained coeff.	**0.556**	**1.003**	0.156	**6.075**	**6.111**	
	P-values	*0.000*	*0.000*	*0.503*	*0.000*	*0.000*	
Health	***constrained coeff.***	**1.485**	**4.155**	**2.032**	**0.683**	**4.608**	*2007*
	P-values	*0.000*	*0.000*	*0.000*	*0.031*	*0.000*	
	unconstrained coeff.	**1.546**	**1.441**	**2.094**	**0.931**	**4.174**	
	P-values	*0.000*	*0.000*	*0.000*	*0.003*	*0.000*	
Finance	***constrained coeff.***	**1.105**	**4.417**	**1.169**	**3.843**	**1.431**	*719*
	P-values	*0.000*	*0.000*	*0.001*	*0.000*	*0.000*	
	unconstrained coeff.	**1.108**	**3.373**	**1.036**	**3.817**	**1.416**	
	P-values	*0.000*	*0.000*	*0.001*	*0.000*	*0.000*	
Other	***constrained coeff.***	**0.964**	**6.549**	**1.151**	**4.511**	**2.089**	*1811*
	P-values	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	
	unconstrained coeff.	**0.999**	**5.113**	**1.491**	**4.611**	**1.919**	
	P-values	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	

Appendix C: Derivation of valuation coefficients for intangible assets

This appendix derives the coefficients in our valuation equation in terms of the other coefficients from the autoregressive equations. The derivation is similar to Ohlson (1999), Barth et al. (1999), and Barth et al. (2005). We demonstrate our procedure using our first system of equations (for hypothesis 1a and b). In the paper, we estimate the following system to investigate value relevance for definite and indefinite intangible assets (*System 1*):

$$Abearnings_{t+1} = \alpha_1 + \omega_{11} Abearnings_t + \omega_{12} Accruals_t + \omega_{13} BVE\_adj_t + \omega_{14} Def\_\text{int}_t + \omega_{15} Indef\_\text{int}_t + \tau_t + \tau_{ind} + e_{1t+1} \quad (1a)$$
$$Accruals_{t+1} = \alpha_2 + \omega_{22} Accruals_t + \omega_{23} BVE\_adj_t + \omega_{24} Def\_\text{int}_t + \omega_{25} Indef\_\text{int}_t + \tau_t + \tau_{ind} + e_{2t+1} \quad (1b)$$
$$BVE\_adj_{t+1} = \alpha_3 + \omega_{33} BVE\_adj_t + \tau_t + \tau_{ind} + e_{3t+1} \quad (1c)$$
$$Def\_\text{int}_{t+1} = \alpha_4 + \omega_{44} Def\_\text{int}_t + \tau_t + \tau_{ind} + e_{4t+1} \quad (1d)$$
$$Indef\_\text{int}_{t+1} = \alpha_5 + \omega_{55} Indef\_\text{int}_t + \tau_t + \tau_{ind} + e_{5t+1} \quad (1e)$$
$$MVE_t = \alpha_6 + \beta_1 BVE\_adj_t + \beta_2 Abearnings_t + \beta_3 Accruals_t + \beta_4 Def\_\text{int}_t + \beta_5 Indef\_\text{int}_t + \tau_t + \tau_{ind} + e_{6t+1} \quad (1f)$$

All variables are defined as in the paper. First, we define **M**, a **5x5** matrix for all coefficients in equations (1a) through (1e), **X**, a 5x1 row vector comprising coefficients of equation (1a), and **Z** = {*BVE_adj, Abearnings, Accruals, Def_int, Indef_int*}, a **1x5** column vector comprising variables of interest in valuation equation (1f) of the system. We also define **T** ={0,0,0,0,1}, a 1x5 row vector, and $\boldsymbol{\alpha}$={0,0,0,0,1}, a 1x5 row vector. Using this notation and following Barth et al. (2005) we solve our equation (1f) conditional on coefficients of **M** for our linear information model in *System 1*. In particular, market value of equity, *MVE,* can be represented by the following equation in matrix notation (see Ohlson, 1999; Barth et al., 2005):

$$\boldsymbol{MVE_t} = \alpha \boldsymbol{Z_t} = (\boldsymbol{T} + \frac{\boldsymbol{X}}{1+\boldsymbol{r}}[\boldsymbol{I} - \frac{\boldsymbol{M}}{1+\boldsymbol{r}}]^{-1})\boldsymbol{Z_t}$$

Where r represents cost of equity capital. For *System 1*, our derivation of *MVE* yields the following theoretical market value equation (equation (1f)) explaining market value of equity in terms of coefficients of the other autoregressive equations (equation (1a) through (1e)), where $\boldsymbol{\alpha}$ is represented by the terms in parentheses:

$$
\begin{aligned}
MVE &= \left(\frac{\omega_{11}}{1+r-\omega_{11}}\right) Abearnings \\
&+\left(\frac{\omega_{11}\omega_{12}}{(1+r-\omega_{22})(1+r-\omega_{11})}+\frac{\omega_{12}}{1+r-\omega_{22}}\right) Accruals \\
&+\left(\frac{\omega_{11}(\omega_{13}r+\omega_{12}\omega_{23}-\omega_{13}\omega_{22}+\omega_{13})}{(1+r-\omega_{11})(1+r-\omega_{22})(1+r-\omega_{33})}+\frac{\omega_{12}\omega_{23}}{(1+r-\omega_{33})(1+r-\omega_{22})}+\frac{\omega_{13}}{1+r-\omega_{33}}\right) BV\_adj \\
&+\left(\frac{\omega_{11}(\omega_{14}r+\omega_{12}\omega_{24}-\omega_{14}\omega_{22}+\omega_{14})}{(1+r-\omega_{44})(1+r-\omega_{22})(1+r-\omega_{11})}+\frac{\omega_{12}\omega_{24}}{(1+r-\omega_{44})(1+r-\omega_{22})}+\frac{\omega_{14}}{1+r-\omega_{44}}\right) Def\_int \\
&+\left(1+\frac{\omega_{11}(\omega_{15}r+\omega_{12}\omega_{25}-\omega_{15}\omega_{22}+\omega_{15})}{(1+r-\omega_{55})(1+r-\omega_{22})(1+r-\omega_{11})}+\frac{\omega_{12}\omega_{25}}{(1+r-\omega_{55})(1+r-\omega_{22})}+\frac{\omega_{15}}{1+r-\omega_{55}}\right) Indef\_int
\end{aligned}
$$

We also derive constrained estimators for the other three systems (*System 2, System 3, and System 4*) using the same procedure. Derived equations are available upon request. The derivation of the cash flow system works in the same manner with the exception that *Cash flow* is substituted for *Accruals*.

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Acquired intangible assets, CAM disclosures, and audit risk

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ABSTRACT:

This paper investigates the association between net values of acquired intangible asset classes, their inherent audit risk, and audit fees. First, our findings using a large and hand-collected sample show that acquired intangibles, in general and especially with definite lifetimes, remain less expensive than the alternative accounting treatment: goodwill. Second, and most important, we show that auditors' use of intangible-related critical audit matters (CAMs) moderates this association in a difference-in-differences design. Intangible assets increase audit fees especially in high litigation industries, but intangible-related CAMs moderate the link between intangible assets and audit fees. These results are consistent with the hypotheses that public disclosure of intangible-related CAMs gives the auditor subject-specific protection against audit risks from acquired intangible assets. This, in turn, allows them to reduce audit fees. Overall, these results are important for auditors, standard setters and also inform researchers regarding the risk-reducing effects of CAM disclosures.

Key words: Intangible assets, auditing, business combinations, critical audit matters
JEL Codes: M40, M42, M48
Data availability: Data are available from the public sources cited in the text

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Acquired intangible assets, CAM disclosures, and audit risk

ABSTRACT:

This paper investigates the association between net values of acquired intangible asset classes, their inherent audit risk, and audit fees. First, our findings using a large and hand-collected sample show that acquired intangibles, in general and especially with definite lifetimes, remain less expensive than the alternative accounting treatment: goodwill. Second, and most important, we show that auditors' use of intangible-related critical audit matters (CAMs) moderates this association in a difference-in-differences design. Intangible assets increase audit fees especially in high litigation industries, but intangible-related CAMs moderate the link between intangible assets and audit fees. These results are consistent with the hypotheses that public disclosure of intangible-related CAMs gives the auditor subject-specific protection against audit risks from acquired intangible assets. This, in turn, allows them to reduce audit fees. Overall, these results are important for auditors, standard setters and also inform researchers regarding the risk-reducing effects of CAM disclosures.

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1. Introduction

The capitalization of acquired intangibles assets[1] remains a major focus of debate in financial accounting (e.g., FASB 2019; IASB 2020). In business combinations, acquirers identify and estimate the fair values for the target's intangible assets and separate these identifiable intangible assets from goodwill (SFAS 141; ASC 805). Proponents highlight the information value of this separation (Ewens et al. 2019; Gu et al. 2023), while the subjectivity and valuation uncertainty exposes auditors to additional audit risk[2]. Yet, we lack systematic evidence on the audit effects of acquired intangibles, especially beyond the acquisition date. It remains unclear whether and how acquired intangibles with indefinite and definite economic lifetimes are reflected differently in audit fees compared to the goodwill and whether auditors can benefit from protection against higher audit risk using intangible-related critical audit matters (CAM) (Brasel et al. 2016; Kachelmeier et al. 2020).

We investigate the audit effects of acquired intangibles using a unique hand-collected sample of acquired intangible assets with their respective net values from 2009 until 2021. Our sample of 2,358 US-nonfinancial firms allows us to observe the breakdown of acquired intangibles by their economic lifetimes (definite vs. indefinite lifetime) and separates them by their respective classes (*tech*, *customer*, *contract*, and *marketing*)[3]. Moreover, it allows us to investigate the audit effects of acquired intangible assets beyond the acquisition date, which incorporates subsequent fair value measurement. The mean ratio of acquired intangibles to total assets is 7.30 percent (standard deviation 10.3 percent) highlighting the economic importance of this balance sheet item. This ratio will continue to rise in the coming years as firms heavily invest in acquiring new technologies such as ChatGPT (Jha et al. 2023).

[1] Throughout we use the terms "acquired intangibles" and "acquired intangible assets" interchangeably.
[2] Throughout we use the terms "audit risk" as an umbrella term of the auditor's adverse consequences in cases of auditor litigation- and reputation risk. Thereby, we also include adverse consequences to the auditor's reputation in those cases as discussed in Bell et al. (2001) and Simunic and Stein (1996).
[3] Both US Generally Accepted Accounting Principles (US GAAP) and International Financial Reporting Standards (IFRS) propose to distinguish intangible assets among those classes.

We measure the audit effects of acquired intangibles through audit pricing and the moderating effects of intangible-related CAMs on the association between acquired intangibles and audit fees. About 9 percent of the observations receive a CAM for their intangible assets, which identify intangibles as a critical position in the audit. Empirically, we examine acquired intangibles as determinants of audit fees in a panel setting (Hribar et al. 2014) and then exploit the introduction of CAMs in a difference-in-difference design.

Our results show a positive link between acquired intangibles and audit fees but with heterogeneous effects among different lifetimes and classes. First, acquired intangibles with indefinite lifetimes, which require annual impairment testing (ASC 350-30), show a strong and positive association with audit fees; while definite intangibles, which are subject to amortization, show a weaker but also positive association with audit fees. This evidence is consistent with higher risk for auditors but also with more effortful audits attributable to indefinite acquired intangibles and their annual impairment testing. We also find that both definite and indefinite acquired intangible assets remain less expensive to audit than goodwill, which provides evidence about potential costs of subsuming more intangibles into goodwill (FASB 2019; IASB 2020).

Turning to the detailed findings regarding audit fees and the different intangible asset classes we establish the following findings: Among indefinite acquired intangibles, marketing intangibles, such as trademarks and brands, show the strongest positive associations with audit fees; while indefinite contract intangibles, such as franchises, show no significant association with audit fees. Among definite acquired intangibles, only definite tech intangibles, such as patent and developed technology, show a strong and positive association with audit fees; while other definite acquired intangibles such as customer, contract, and marketing intangibles are not significantly associated with audit fees. This evidence indicates that the claim voiced in comment letters that acquired intangibles are more time-consuming and, consequently, more expensive to audit compared to goodwill seems not to be valid for many intangible asset classes (Clor-Proell et al. 2022).

Based on these results we turn to our main question, i.e., the impact of CAMs on audit fees. We use the introduction of CAMs in 2019 and 2020 (Brasel et al. 2016; Kachelmeier et al. 2020; Brown et al. 2020) in a quasi-natural setting to investigate how the link between acquired intangibles and audit fees changes around the disclosure of intangible-related CAMs. The issuance of (subject-specific) CAMs can give the auditor additional protection when dealing with client audit risk by publicly disclosing and discussing areas of firms that were challenging to audit, subjective to value, and complex.[4]

Descriptively, we find that intangible CAMs are longer than CAMs on tangible assets or other complex accounting issues such as taxes. Furthermore, a content analysis shows that they more often highlight the use of valuation experts consistent with the idea to provide a legal safeguard to the auditor in cases of auditor lawsuits. Turning to audit fees, our results indicate that the auditors react to the perceived reduction in audit risks towards acquired intangibles from the public disclosure of intangible-related CAMs by lowering the fee premium for audits with these intangibles. While we acknowledge that other forces might be at work, we interpret this finding as evidence that audit risk of auditors is most likely to explain our results.

Our results remain robust regarding many different specifications. First, we use placebo tests to verify that our moderation effect of CAMs is attributable to CAMs that directly target intangible asset matters and no overall effect that relates to any CAM. Second, we mitigate the effects of potential extreme observations on our results using robust regression designs (Leone et al. 2019; Gassen and Veenman 2023). Third, firms' selection of the auditor or auditor self-selection can be influenced by the level of acquired intangibles. We mitigate this concern by adding audit-firm fixed effects to the regressions. When using robust regressions or adding

[4] First anecdotal evidence from legal cases provides strong support for the negative link between CAMs and auditor risk through higher litigation risk (see WSJ 2023).

audit-firm fixed effects to our main analyses, the inferences do not change with regard to our results. Fourth, we exclude the year 2018 in our identification strategy. In 2018, auditors began to identify client areas where they intended to issue CAMs, but did not disclose this information to the public (Center for Audit Quality 2018). Even without CAM disclosures in 2018, the dry runs may have affected the auditor-client relationship in terms of audit pricing and in many other dimensions. Results, again, remain qualitatively unchanged, when excluding the year 2018. Fifth, impairment pressure might moderate the effect of intangibles and goodwill on the audit risk. In additional tests, we test our results for firms with high and low overall impairment pressure (Li and Sloan 2017; Kim 2023) and find that intangibles remain less expensive than goodwill for both subsamples. Sixth, one might argue that the audit process of firms with intangible assets is significantly different to firms that do not have acquired intangible assets driving our results. Put differently, one might argue that we bias our findings in our favor by comparing firms with large intangibles to firms that do not have any intangibles at all. To alleviate these concerns, we re-estimate our results for firm years only, that have positive acquired intangible asset amounts. Results remain qualitatively the same.

Our study provides two major contributions to the literature. First, we contribute to the literature on the overall effects of capitalizing the different classes and lifetimes of acquired intangibles (FASB 2019; IASB 2020) by providing evidence on their audit effects. Audit fees are very useful in assessing the audit-level consequences of capitalizing acquired intangibles as inputs into audits. They capture the auditor's perception of a client and the reliability of the client's accounting (Hribar et al. 2014; Ayres et al. 2019; Francis 2011; Zhang 2018). In our tests, we use the association between audit fees and goodwill as our benchmark because the subsuming of the acquired intangibles into goodwill is the most obvious alternative accounting treatment.[5] Our results are informative about partially subsuming different acquired intangible

[5] Our study extends the findings by Datta et al. (2020) among several dimensions. First, we investigate the audit effects of acquired intangibles with different economic lifetimes and classes. Given that acquired intangibles combine very heterogeneous asset classes and are partially subject to the impairment-only approach and partially

assets into goodwill, as discussed by FASB (2019) and IASB (2020). Subsuming all acquired intangibles into goodwill arguably results in an unambiguous decrease in audit workload and/or less audit risk (Koh et al. 2022; Beck et al. 2022) and thus lower audit fees. However, an accounting item that comingles all different types of intangibles assets might require at least the same amount of work by the auditor to still determine the correct impairment amount and calculate potential offsetting effects (Pickerd and Piercey 2021; Libby and Brown 2013). In addition, auditors frequently rely on summary metrics (e.g., earnings, revenues or assets) to assess materiality for the financial statement (Eilifsen and Messier 2015), questioning whether disaggregation may have an impact on auditors' materiality judgments and therefore on audit fees. While our results show that whole intangible assets are positively associated with audit fees, our unique datasets including the detailed breakdown into different intangible asset classes and lifetimes shows for the first time that this effect is driven by technology definitely-lived and customer definitely-lived intangible assets.

Second, and most importantly, we contribute to the young and growing literature on CAMs, which shows partially conflicting results regarding the role of CAMs. In particular, while Klevak et al. (2023) provide evidence that firms with more extensive CAM disclosures are associated with increased perceived uncertainty, Burke et al. (2023) highlight important impacts on CAM-driven disclosure effects, but acknowledge limited capital market effects. We contribute to this literature by showing that our results are consistent with results that auditors use CAMs to mitigate their audit risk. For instance, KMPG faces severe litigation cases after failing to issue a CAM for the rising risks in the deposit position of the Silicon Valley bank (SVB).[6] Moreover, Brasel et al. (2016) provide theoretical and early experimental evidence on

to amortization, disaggregated information on acquired intangibles allows us to uncover effects that are averaged when only considering the aggregated amount of all intangibles. Thus, we particularly inform the current debate in standard setting (FASB 2019). Second and most important, we are the first to analyze the role of CAMs in this setting.

[6] In the 2023 lawsuits (City of Hialeah Employees' Retirement System vs. Becker et al. (2023) Case 3:23-cv-01697), KPMG was sued, among others, for the lack to "*identify risks associated with SVB's declining deposits or SVB's ability to hold debt securities to maturity*" as a CAM. For an excerpt of the original text from the filing, see Online Appendix OA1.

the protective effects of CAM disclosures on auditors' litigation risk in cases of undetected fraud. Brown et al. (2020) and Kachelmeier et al. (2020) show that area-specific CAM disclosures reduce the jurors' assessment of the audit firm's culpability in lab experiments. The effects are concentrated on CAMs in the areas that involve high measurement uncertainty (Kachelmeier et al. 2020) and are consequently well suited to inform our investigations in the context of acquired intangibles.[7] Nevertheless, Li and Luo (2023) and Reid et al. (2019) show a positive or zero effect of the number of CAMs on the overall level of audit fees. We complement the literature by showing how the disclosure of intangible-related CAMs moderates the link between the acquired intangibles and audit fees. Thereby, our empirical evidence based on archival data strongly supports earlier experimental evidence by Brasel et al. (2016), Brown et al. (2020), and Kachelmeier et al. (2020). Furthermore, our results reconcile the theoretical and experimental findings with partially contradicting archival evidence from Li and Luo (2023) and Reid et al. (2019) by showing that it is not necessarily the direct effect on audit fees but the area-specific premium on audit fees that is affected by area-related CAM disclosures.

[7] The international evidence from other legislations and institutional environments is less clear. Reid et al. (2019) do not find a direct link between the reporting requirements of auditors in the United Kingdom, which are arguably similar to the CAM disclosure, and the firms' overall audit fees. Nevertheless, auditor litigation risk in the UK substantially differs from that in the US.

2. Institutional framework and hypotheses: The different acquired intangible assets

2.1 Institutional framework

Acquired intangible assets and their assurance differ from other assets on the balance sheet in significant ways. In general, standard setters define intangibles as nonfinancial assets that lack physical substance (ASC 350, IAS 38). Although many internally generated intangibles such as research and development (R&D) and advertising expenditures are expensed when incurred, acquired intangibles from individual transactions or business combinations are capitalized on the statement of financial position and amortized or tested for impairment over time. The issuance of SFAS 141 and SFAS 142 in 2001 changed the accounting standards for acquired intangibles. These standards heavily affected the auditing processes of firms, since billions of intangible assets have been added to acquiring firms' balance sheets (McInnis and Monsen 2021; Landsman et al. 2022). The accounting treatments of intangibles in SFAS 141 and SFAS 142 have remained largely constant since 2001 in which they mandate that acquirers capitalize acquired intangibles under the purchase method. But in 2007, the FASB revised the reporting and disclosure requirements regarding the accounting for business combinations (Andrews, Falmer, Riley, Todd, and Volkan 2009). SFAS 141R mandates that acquiring firms capitalize in-process R&D as an indefinite intangible asset until the completion or abandonment of the purchased R&D project.[8] Currently, both the FASB and IASB continue debating whether the accounting for acquired intangibles should be updated given their rising importance to firms' balance sheets (Landsman et al. 2022).

For acquired intangibles from business combinations, acquirers must identify and estimate fair values of the target's assets. Acquired intangibles are identifiable when they are contractible (contractual or legal criterion) or separable from the entity (separability criterion) (ASC 805

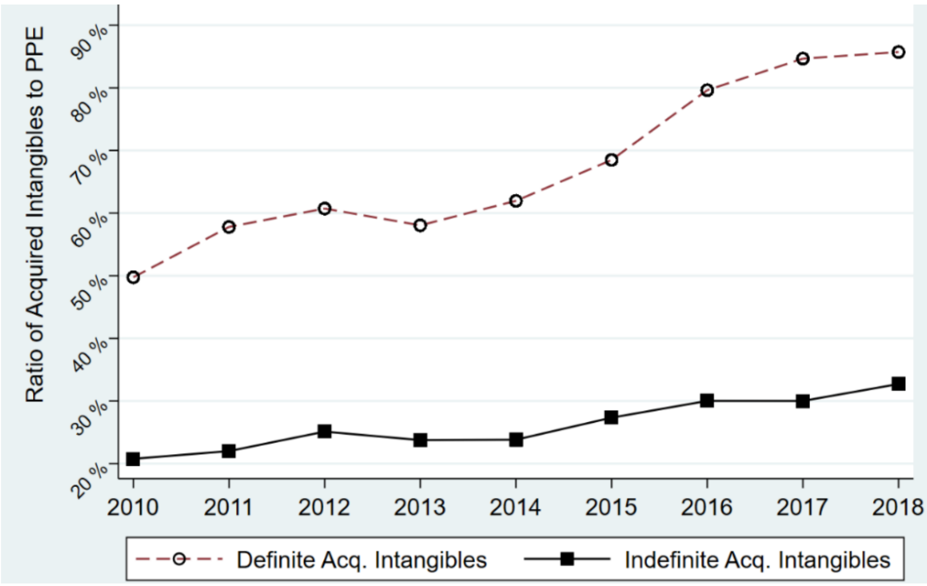
[8] In 2014, the FASB relaxed the accounting of acquired intangibles for private firms only due to high costs (*ASU No. 2014-18*). In particular, they allowed the subsuming of customer intangibles and non-compete agreements into goodwill, and goodwill can either be amortized or be subject to annual impairment testing. Because our sample covers only publicly listed firms, these changes do not affect the accounting treatment for our sample.

and 820). A purchased trademark is an identifiable intangible asset because it is contractible given its legal nature and can be sold separately. In contrast, merger synergies are not identifiable as acquired intangibles because they are not contractible and cannot be separated from the firm. Both the FASB and the IASB specify five different classes of intangibles in their framework: *tech*, *customer*, *contract*, *marketing*, and *artistic*. A detailed explanation with examples for each of the different classes of acquired intangibles is provided in Online Appendix OA2.

When recognized, acquirers have to determine the useful economic lifetimes of acquired intangibles (ASC 350). Usually, the economic lifetime is the period during which an intangible asset is expected to contribute to the acquirer's future cash flows (Reilly and Schweihs 2014). For acquired intangibles, the economic lifetime, either definite or indefinite, can be assessed through their legal, regulatory, or contractual duration, or their expected uses (ASC 350-30-35-3). Figure 1 shows the development of acquired intangibles as a share of property, plant and equipment (PPE) over time. It illustrates that the importance of acquired intangibles compared to more classic assets, such as PPE, has substantially increased for both acquired intangibles with definite as well as indefinite economic lifetimes. Online Appendix OA3 shows the similar figure for each acquired intangible class.

Figure 1: Growth of definite and indefinite acquired intangibles in relation to property, plant & equipment

This graph illustrates the growth of definite and indefinite acquired intangibles in relation to property, plant, and equipment (PPE) over time (2010-2018).



For acquired intangibles with a definite economic lifetime, such as customer contracts with a fixed term or patents with an expiration date, the firm amortizes these assets over their remaining lifetime (for a more detailed description, see Reilly and Schweihs (2014)). In the case of unforeseen events or circumstances, definite intangibles are also tested for impairment when an impairment may be probable (ASC-360-10-35-21).

Indefinite acquired intangibles, on the other hand, have an undetermined economic lifetime and are subject to annual impairment testing instead of amortization. Common examples of these intangibles are licenses and trademarks. Such as a goodwill impairment test, the impairment test for indefinite intangibles consists of the same steps where the fair value of the underlying intangible asset is compared with the carrying amount. Therefore, an impairment loss is recognized when (1) the carrying amount of an acquired intangible asset is not recoverable and (2) the carrying amount of an indefinite acquired intangible asset exceeds its fair value. Because intangibles typically lack market benchmarks, the impairment test of their carrying amounts involves managerial discretion and a substantial amount of judgement, which makes indefinite acquired intangibles similar to other level 3 fair value measurements, for example, financial instruments (Ettredge et al. 2014; for more details, see Beatty and Weber 2006).

2.2 Hypotheses development

The assurance of acquired intangibles resembles that of other complex fair value measurements (FVM) in that it is highly demanding and bears multiple risks for the auditor (Griffith 2020; Ettredge et al. 2014; Cannon and Bedard 2017; Datta et al. 2020). Acquired intangibles are carried on firms' balance sheets at the lower of their historical costs and their FVM. With the FVM, auditors are most concerned about whether that value is close to or even drops below its carrying value. The FVM of intangibles often lack reliable market benchmarks but frequently rest on internal valuations models without market inputs (level 3 FVM, henceforth L3FVM) resulting in very demanding auditing task. Online Appendix OA4 provides three examples of accounting related lawsuits that center around the accounting treatment of intangible assets. In particular, they underline the inherent audit risk associated with acquired intangible assets.

The Public Company Accounting Oversight Board (PCAOB) requires auditors to adapt procedures to the client's risks of material misstatements (PCAOB AS 2301) and thereby puts a special focus on accounting estimates, such as L3FVM (AS 2501)[9]. The auditor should perform at least one of three substantive procedures, either individually or in combination: (a) *Test the firm's process used to develop the accounting estimate;* (b) *develop an independent expectation for comparison to the firm's*; or (c) *evaluate audit evidence from events or transactions occurring after the measurement date related to the accounting estimate for comparison to the firm's estimate* (PCAOB AS 2501). Although the auditor is only required to

[9] Previously, AS 2501 together with AS 2502 outlined the auditors' requirements. In 2019, the PCAOB issued a revised AS 2501 that also includes requirements previously included in AS 2502.

use one of the approaches, most auditors rely on at least two of them in cases of the L3FVM (Glover et al. 2017).

Both the more extensive audit effort as required by the PCAOB and the higher audit risk of intangibles for auditors is associated with higher fees required by the auditor (Mohrmann et al. 2019; Hribar et al. 2014). The auditor can potentially reduce parts of the premium on audit risk by inducing more effort through longer hours (Zhang 2018; Bell et al. 2001) or relying more on valuation specialists (external or in-house). Nevertheless, valuation specialists reduce audit risk only partially as the audit is primarily the partners' responsibility (Glover et al. 2017; Griffith 2020). Furthermore, the L3FVM has highly uncertain and subjective estimations that rely on significant and complex assumptions (Kanodia et al. 2004). Further, these estimations come from multiple valuation techniques (Cannon and Bedard 2017) that are somewhat difficult to objectively verify, even if the audit effort is very high. Hence, it is unclear whether auditors in the context of intangibles can efficiently reduce risk by increasing the effort put into the audit given the complexity of the models (Bratten et al. 2013; Cannon and Bedard 2017; Christensen et al. 2012). For these reasons, our first hypothesis predicts in alternative form:

Hypothesis 1: The acquired intangibles are positively associated with audit fees.

Within the group of intangibles the economic lifetime heavily influences audit risk and effort to perform an adequate assurance. Acquired intangibles with a definite lifetime are amortized over their respective economic lifetime and only show additional impairments at unforeseen events and circumstances (ASC 350). The predetermined amortization scheme decreases the definite intangibles' carrying values mechanically over time. Thereby, these assets become economically less relevant and an impairment becomes less likely. Thus, definite intangibles will be easier to audit than indefinite intangibles.

In contrast, indefinite acquired intangibles have a useful lifetime, which is either unlimited or at least not specified at the reporting date. Just like the impairment test for goodwill, impairment tests for indefinite intangibles are based on subjective and complex assumptions that require managerial discretion (Shalev et al. 2013; Koonce et al. 2021). The assurance of indefinite acquired intangibles requires the auditor to test the subjective assumptions of management every year and, consequently, exposes the auditor to audit risk in every reporting period.

On the one hand, one can expect the impairment test for indefinite intangibles to show the same attributes as the goodwill impairment test. Put differently, annual impairment testing requires the same audit effort for goodwill because of their highly subjective valuations and untimely recognition of impairment losses. These losses could cause additional audit risk. On the other hand, indefinite intangibles such as trademarks can be valued more easily because their projected cash flows are easier to quantify. For these reasons, we separate our expectations into two hypotheses:

Hypothesis 2.1: Definite acquired intangibles are less associated with audit fees than goodwill.

Hypothesis 2.2: Indefinite acquired intangibles are less or equally, but not more associated with audit fees than goodwill.

Turning to our investigation of critical audit matters (CAMs), the auditor can use different measures that reduce its audit risk (Carcello and Palmrose 1994; Krishnan and Krishnan 1997; Seetharaman et al. 2002; Venkataraman et al. 2008). We argue that the public disclosure of intangible-related CAMs discourages lawsuits against the auditor even if this is not its main purpose. Starting in 2019 and 2020, auditors could publicly express subject-specific CAMs. With the introduction of CAM reporting, the auditor informs the public about relevant areas that were especially challenging, subjective, or complex to audit (PCAOB Release No. 2017-001) and that might deserve more attention from investors. Because CAMs express the auditor's concerns in a specific area that is considered as judgmental and complex but not necessarily incorrect, CAMs help the auditor to document the awareness and potential measures in these areas (already Carcello and Palmrose (1994) make a similar case for modified audit opinions). Anecdotal evidence for the link between CAMs and audit risk also comes from the 2023 lawsuit against KPMG after they failed to identify the relevant CAMs for the Silicon Valley Bank (WSJ 2023). Appendix B provides a real-world example of how Ernst & Young LLP (EY) documented awareness of CAMs for the acquired intangibles of Walmart Inc. in 2021. EY also informed the shareholders on how (substantially) it addressed these matters in their audit and made clear that it had conducted the appropriate and substantial procedures necessary.

CAMs might provide valuable protection against audit risk (Brasel et al. 2016; Vinson et al. 2019; Kachelmeier et al. 2020) from intangibles that are hard-to-verify and complex nonfinancial assets and require the L3FVM (Kachelmeier et al. 2020). Brasel et al. (2016) show that relative to stating there were no CAMs, their disclosure provides litigation protection in cases of undetected fraud. Kachelmeier et al. (2020) show that the auditor's litigation risk decreases especially in CAM areas that involve highly uncertain measurement such as valuations of intangibles. Burke et al. (2023) show that CAMs also improve the overall reporting quality by inducing better and more detailed managerial disclosure on the CAM area that helps inform the market. Brown et al. (2020), in contrast, focus on the audit firm's culpability and show that subject-specific CAM disclosures substantially reduce the jurors' assessments of that culpability. In sum, these studies support the idea that CAMs reduce audit risks and in turn are associated with lower fees.

Nevertheless, the issuance of CAMs can also come with costs for both the auditor and firms. Similar to other adverse disclosures by the auditor about the firm's financial statements (Carcello and Neal 2003; Vanstraelen 2003; Krishnan 1994; Bleibtreu and Mohrmann 2019), the excessive disclosure of CAMs might induce firms to subsequently change their auditor. Furthermore, removing subject-specific CAMs can increase the audit risk for these subject areas of the audit in subsequent years (Vinson et al. 2019). Therefore, auditors might have an incentive not to communicate critical accounting positions, such as acquired intangibles, to the public. Overall, the impact of the CAMs regarding the effect of acquired intangibles on audit fees is an empirical question. Our third hypothesis predicts in alternative form:

Hypothesis 3: If audit firms publicly disclose critical audit matters about acquired intangibles, then the audit fee premium for acquired intangibles will decrease.

3. Research design, sample selection, and data description

3.1 Research design

To test our three hypotheses, we estimate two different specifications: an audit fee model to determine how acquired intangible assets differ in their pricing and an identification strategy around the critical audit matter (CAM) concerning intangibles to identify the impact of CAMs on the relation of acquired intangibles and their audit pricing.

3.1.1 The audit fee model

We estimate the associations between acquired intangibles (goodwill) and audit fees using a linear regression model with controls for the client and client-auditor-engagement factors that other studies have established to determine audit fees (Hribar et al. 2014; Zhang 2018). We use a one-stage approach and include all variables in a single regression similar to Zhang (2018) because the use of regression residuals as dependent variables poses several challenges when the estimation errors are large (Chen et al. 2018).

We estimate equation (1) as pooled-OLS model with industry (Fama-French 48 industry) and year fixed effects with standard errors clustered at the firm level (Petersen 2009). Later, we test the robustness of our results using a robust regression design (Leone et al. 2019) and including audit-firm fixed effects. Thus, we estimate the following model (variable definitions can be found in Appendix A):

$$Ln\ (Audit\ Fee)=\beta_0+\beta_1 Acquired\_Int_{i,t}+\beta_2 Goodwill_{i,t}+Controls$$

$$+\ Industry\ FE+\ Year\ FE+\mathrm{e}_{i,t} \tag{1}$$

where the natural logarithm of the audit fees (*Ln (Audit Fee)*) is the dependent variable.

The total amount of acquired intangibles (*Acquired_Int*) is our main independent variable of interest. We scale acquired intangibles by total assets to allow for a better comparison of the coefficients and to mitigate scaling effects. Furthermore, we break down acquired intangibles by their economic lifetime (*Def_Int*, *Indef_Int*) for the tests of hypothesis 2 and by their respective classes (*Share Tech Indef, Share Contract Indef, Share Tech Def, Share Customer Def, Share Contract Def, Share Other Intangibles*). We compare the coefficients for the different measures of acquired intangibles with the coefficient for the firms' amount of goodwill that is scaled by total assets (*Goodwill*).

We control for the other drivers of audit fees from the literature (Ayres et al. 2019; Hribar et al. 2014; Zhang 2018; Badertscher et al. 2014; Minutti-Meza 2013). We especially control for the natural logarithm of sales[10] (*Size, Employees*), the profitability (*ROA*), the cash ratio (*CashR*), the sales growth (*SalesGrowth*), the current ratio (*CurrentR*), the share of foreign sales (*Foreign*), leverage (*Leverage*), loss years (*Loss*), firms' smoothing incentives (*Smooth*), mergers and capital issuances activities (*Merger; IPO; SEO*), the value of inventory and receivables (*InvRec*), the special items (*Special Items*), firm's complexity (*BusinessSegment*), a television industry indicator (*TV_Industry_Ind*)[11], the market valuation (*BTM*), restatements

[10] Results remain qualitatively unchanged, if we use the natural logarithm of total assets (Hay et al. 2006) instead of sales to capture firm size. Because we scale many control variables by total assets, the natural logarithm of sales might yield more robust results.

[11] Among television broadcasters, FCC licenses, which are an indefinite intangible asset, are the most important asset and are more liquid than other intangible assets in other industries. Therefore, they appear to be better audited and therefore would distort our average results. We estimated our results without this industry and get the same inferences.

(*Restatement*), the ratio of non-audit fees (*NAF*), the Big 4 and industry expert auditor (*Big_N; IndLeader_Fee*), December fiscal year-end (*Busy Season*), the audit opinion (*Audit Opinion*), the audit timeliness (*AuditTimeliness*), internal control weakness (*WEAK_404*), the litigation environments from Francis et al. (1994) (*Litigation*), and previous accounting-related lawsuits (*PrevLawsuits*). To mitigate the effect of extreme observations, we winsorize our dependent and independent variables on the 1st and 99th percent levels.

In additional tests, we also interact our main independent variable, either the total amount of acquired intangibles (*Acquired_Int*) or the acquired intangibles with a definite or an indefinite economic lifetime (*Def_Int, Indef_Int*), with *#AccLawsuits*, a variable that captures the client`s accounting-related lawsuits[12] in the 12 months after the annual report had been published following Datta et al. (2020). Because client's accounting-related lawsuits easily allow plaintiffs to sue the audit firm in state-law negligence cases (Donelson 2020) and negligence cases shape audit risk (Pickerd and Piercey 2021; Donelson 2020), this measure captures auditor litigation risk much broader than direct securities class action (Maksymov et al. 2020). Because we obtained data on all ongoing lawsuits and some last for many years, we take the change in the ongoing lawsuits to better capture the change in audit risk that relate to the current accounting numbers.

3.1.2 CAM Introduction

We use the introduction of CAMs as an identification strategy. Prior to the CAM introduction, auditors only had limited abilities to communicate critical positions to the public. The introduction of CAMs provided the auditor a new tool to guide the public's attention to the reporting areas of firms that were challenging to audit, subjective to value, and complex, such as acquired intangible assets. In our research design, we use a triple interaction with our main independent variables to exploit the first-time disclosures of CAMs in 2019 and 2020.

[12] We refrain from using the clients' actual statements as our measure for auditor litigation risk because empirical evidence suggests that the link between client's restatements and auditor litigation risk turns non-significant in more recent data (Lennox and Li 2020).

Therefore, we interact them with a static and binary variable that takes the value of one if the firm received a CAM in 2019 or 2020 for its acquired intangibles (*CAM_int*) as our first interaction, and also interact it with an indicator variable (*Post*) for the years after the CAM had been disclosed. We follow deHaan et al. (2023) and estimate our model with interaction effects for each control variable to control for unobserved heterogeneity. Thus, we employ the following regression in a difference-in-differences design:

$$Ln\ (Audit\ Fee_{it}) = \beta_0 + \beta_1 Acquired\_int_{i,t} \times CAM\_int_i \times Post_t + \beta_2 Acquired\_int_{i,t} \times CAM\_int_i$$
$$+ \beta_3 CAM\_int_i \times Post_t + \beta_4 Acquired\_int_{i,t} \times Post_t + \beta_5 Acquired\_int_{i,t} + \beta_6 CAM\_int_i$$
$$+ \beta_7 Post_t + \beta_8 Goodwill_{i,t} + Controls + Industry\ FE + Year\ FE + e_{i,t} \tag{2}$$

where the natural logarithm of the audit fees (*Ln (Audit Fee)*) is the dependent variable. Our coefficient of interest is the triple interaction of acquired intangibles, CAM disclosure, and the *Post* indicator. All control variables are the same as those in equation (1). Again, we cluster our standard errors by firm.

3.2 Sample and descriptive statistics

We construct our sample by first obtaining accounting and audit data from Compustat North America and Audit Analytics for the period from 2009 to 2021. Our sample begins in fiscal year 2009 to keep the reporting and disclosure requirements of acquired intangibles fixed (Andrews et al. 2009). We require firms to have non-missing equity book values, total assets, net income, date of the signature by the auditor, and audit fees. Additionally, we exclude firms with market values of equity of less than USD one million. We also restrict our sample to nonfinancial firms because the auditing for financial firms such as banks and insurance firms differs substantially (Hribar et al. 2014; Ettredge et al. 2014) and we exclude firm years with audit delays of more than 365 days because the audit delays most likely refer to audit revisions and not to the initial audit.

Lastly, we retain data on the CAMs from Audit Analytics. In the US, firms marked as accelerated filers could receive a CAM from their auditors starting in 2019, while smaller firms could receive CAMs starting in 2020. We identify intangible-related CAMs when CAM topics in Audit Analytics are marked as “Intangible assets” and “Goodwill and intangible assets”. We also include CAMs with the topic “long-lived assets”, when they contain information about critical intangible asset positions.[13] We manually verify each intangible-related CAM to make sure that it contains information on the acquired intangibles that have been capitalized on the balance sheets. Appendix B contains an example of an intangible-related CAM for Walmart Inc. (2021).

We combine these data sources with the hand-collected database from Landsman et al. (2022). This database contains the *net amounts* of acquired intangibles from the notes of annual financial statements obtained from the SEC Edgar webpage. Online Appendix OA5 provides

[13]Audit Analytics sometimes categorizes CAMs for both tangible and definite intangible assets under the category “long-lived assets”. To identify intangible-related CAMs within this category, we follow a two-step procedure. In the first step, we identify CAMs about intangible assets using text word searches for the words “intangible assets” and “intangibles”. In the second step, we manually verify each CAM to make sure that each intangible-related CAM identified is indeed about acquired intangible assets.

an example of a disclosure of acquired intangibles for Amazon Inc. (2018). The sample comprises the firms with the largest market capitalizations and covers at least 50% market capitalization in each of the Fama-French 12 industries. More details on the collection process can be found in Landsman et al. (2022).

Panel A of Table 1 presents descriptive statistics of our main independent variable, audit fees, and of our acquired intangible variables. The main sample contains of 18,931 firm-year observations of 2,358 firms.[14] Panel B presents the descriptive statistics for our control variables.

Table 1: Descriptive statistics

Table 1 provides the descriptive statistics for the dependent and independent variables used in this study. Panel A presents our dependent and our different intangible asset variables. Panel B presents the descriptive statistics for all our control variables. The definitions of the variables can be found in Appendix A.

Panel A: Descriptive statistics on dependent and main independent variables (N = 18,931)

Variables	*Mean*	*SD*	*Median*	*p75*	*p90*	*p95*
Dependent variable:						
Ln (Audit Fee)	14.321	1.181	14.340	15.108	15.801	16.260
Scaled intangibles:						
Acquired_Int	0.073	0.1030	0.030	0.105	0.208	0.287
Indef_Int	0.026	0.069	0.000	0.014	0.078	0.165
-Share Marketing Indef	*0.142*	*0.264*	*0.000*	*0.162*	*0.567*	*0.837*
-Share Tech Indef	*0.010*	*0.057*	*0.000*	*0.000*	*0.000*	*0.025*
-Share Contract Indef	*0.051*	*0.192*	*0.000*	*0.000*	*0.012*	*0.538*
Def_Int	0.045	0.066	0.016	0.065	0.136	0.188
-Share Tech Def	*0.036*	*0.083*	*0.000*	*0.029*	*0.114*	*0.201*
-Share Marketing Def	*0.097*	*0.167*	*0.002*	*0.128*	*0.333*	*0.48*
-Share Customer Def	*0.194*	*0.218*	*0.117*	*0.349*	*0.515*	*0.624*
-Share Contract Def	*0.056*	*0.153*	*0.000*	*0.007*	*0.188*	*0.405*
-Share Other Intangibles	*0.049*	*0.149*	*0.000*	*0.017*	*0.110*	*0.300*
Goodwill	0.136	0.151	0.083	0.226	0.367	0.448

[14] For example, in 2017, our sample represents more than 65% of total market capitalization of the US stock market.

Panel B: Descriptive statistics on further control variables (N = 18,931)

Control variables	*Mean*	*SD*	*P25*	*Median*	*p75*	*p90*	*p95*
Size	7.259	2.020	5.942	7.327	8.626	9.835	10.521
ROA	0.007	0.157	-0.007	0.039	0.078	0.129	0.170
CashR	0.183	0.206	0.038	0.107	0.248	0.483	0.654
Sales Growth	0.101	0.369	-0.035	0.051	0.155	0.346	0.560
Special Items	0.019	0.042	0.000	0.005	0.017	0.045	0.086
InvRec	0.235	0.173	0.094	0.204	0.332	0.480	0.584
BTM	0.536	0.474	0.234	0.414	0.675	1.039	1.396
CurrentR	2.561	2.231	1.285	1.929	2.973	4.939	6.903
Foreign	0.034	0.063	0.000	0.006	0.040	0.101	0.158
Leverage	0.423	0.193	0.279	0.421	0.557	0.684	0.758
Loss	0.411	0.492	0	0	1	1	1
Restatement	0.083	0.276	0	0	0	0	1
NAF	0.202	0.236	0.035	0.121	0.282	0.507	0.704
Big_N	0.815	0.388	1	1	1	1	1
Busy Season	0.709	0.454	0	1	1	1	1
Employees	2.801	2.803	0.933	1.957	3.564	6.325	8.585
Smooth	0.232	0.422	0	0	0	1	1
Previous_Lawsuit	0.186	0.389	0	0	0	1	1
Merger	0.362	0.481	0	0	1	1	1
IPO	0.009	0.093	0	0	0	0	0
SEO	0.095	0.293	0	0	0	0	1
Litigation	0.342	0.474	0	0	1	1	1
Audit Opinion	0.227	0.419	0	0	0	1	1
WEAK_404	0.045	0.207	0	0	0	0	0
Tenure	3.572	1.327	2.646	3.464	4.472	5.385	6.083
Business Segment	2.268	0.958	1.732	1.732	3.000	3.606	3.873
Audit Timeliness	4.063	0.204	3.970	4.060	4.174	4.317	4.443
IndLeader_Fee	0.279	0.449	0	0	1	1	1
TV_Industry_Ind	0.010	0.101	0	0	0	0	0

Turning to Table 1, Panel A, our descriptive results confirm the evidence in Figure 1 that definite acquired intangibles are more common than indefinite acquired intangibles. Regarding the classes, we find that definite tech, definite customer, and indefinite marketing are the most common classes of acquired intangibles on balance sheets. However, the results indicate that acquired intangibles are concentrated in bigger firms. In our smaller sample, we use only the years around the introduction of the CAMs, that is, 2015 to 2020. The industry distribution and the major descriptive statistics remain qualitatively similar. Appendix A provides the definition of each variable. All variables are in line with prior research (Ayres et al. 2019; Hribar et al. 2014; Zhang 2018; Badertscher et al. 2014; Minutti-Meza 2013). Online Appendix OA6 provides the industry breakdown and further absolute amounts regarding the main variable of interests, acquired intangible assets.

4. Results

4.1 Acquired intangible assets and audit fees

As a first step, we test hypotheses one and two, i.e., we investigate the association between acquired intangibles and audit fees. As a second step, we test hypothesis three, i.e., we investigate the conditional effect of audit risk on the association between acquired intangibles and audit fees. We use the change in the logarithm of one plus the actual accounting-related lawsuits (#AccLawsuits) within the next twelve months as our main proxy for audit risk. The number of lawsuits indicates the severity of audit risk apparent within a firm. Table 2 shows the multivariate results from estimating equation (1). All uneven columns display the overall effects and all even columns show the conditional effects for high audit risk.

In columns (1) and (2) of Table 2, we report the association of the overall level of acquired intangibles (*Acquired_Int*) with audit fees. In columns (3) and (4), we separate the overall level of acquired intangibles into either those with an indefinite (*Indef_Int*) or those with a definite economic lifetime (*Def_Int*). We predict in hypothesis 2 different effect strengths of acquired intangibles in their audit pricing based on their economic lifetime. In columns (5) and (6), we further test whether within the indefinite and the definite acquired intangibles there is effect heterogeneity regarding the underlying intangible asset classes. For doing so, we follow the approach by Goncharov, Riedl, and Sellhorn (2014) and include the relative share of the different intangible assets classes on the total acquired intangibles as additional variables. We use the share of marketing intangibles as our reference group because this class of intangible assets contains similar assets within the intangible assets with definite and indefinite lifetimes. This division allows us to investigate differences within pricing of the acquired intangibles in firms' audit fees.

We find a positive and statistically significant relation between the overall level of acquired intangibles and audit fees in columns (1) of Table 2. With a coefficient of 0.336 (p-value < 0.01), a one standard deviation increase in *Acquired_Int* results in an increase in the firm's audit fees by four percent. This effect yields strong support for hypothesis 1 and shows that firms' net amounts of acquired intangibles have significant and sizable audit effects. Comparing the effect of *Acquired_Int* with that of *Goodwill* in additional tests, we find that the regression coefficient of acquired intangibles is only about half the size of that from the goodwill (0.336 compared to 0.611) and is also statistically significantly lower than *Goodwill* at the 5 percent level (H_0: coef $_{Acquired\ Int}$- coef $_{Goodwill}$ >= 0.275; p-value = 0.018). In economic terms, this translates into an increase of the audit fees by 4.0 percent per one standard deviation increase in intangible assets compared to an increase of 8.6 percent if the same assets would be subsumed under goodwill. This difference is economically significant and meaningful. From this additional test, we find that auditors price goodwill and intangibles differently and charge lower premiums for intangibles compared to goodwill. In column (2) of Table 2, we find a significantly higher audit fee premium for intangible assets in case of higher audit risk (coefficient on the interaction term= 0.126; p-value < 0.05). Overall, the results from columns

(1) and (2) of Table 2 show that auditors charge higher fees for auditing acquired intangibles and audit risk associated with intangibles further increases audit fees.

When splitting up the intangible assets by their economic lifetime in columns (3) and (4), we find that the coefficients for both *Indef_Int* and *Def_Int* show positive and statistically significant associations with audit fees. More importantly, both coefficients show distinct magnitudes with definite intangible assets (0.331) being cheaper to audit than indefinite intangible assets (0.420). The results point towards differing efforts and risks in the audit regarding acquired intangibles with definite and indefinite economic lifetimes. This evidence is also consistent with indefinite intangible assets, which are subject to annual impairment testing, are being harder to audit than definite intangibles, which are amortized. Again, *Goodwill* possesses the largest coefficient (0.606) underlining that auditing the goodwill is more complex than auditing acquired intangibles. In additional tests, we find that definite intangible assets are significantly different from goodwill (p-value < 0.1) and the difference between indefinite intangible assets and goodwill remains just below conventional significance levels (p-value =0.125). In column (4), we see once more that the effect is heavily driven by firms' audit risk. In economic terms, the effect of column (3) translates into an increase of the audit fees 3.6 percent for one standard deviation of indefinite intangible assets and 2.6 percent [15]for a one standard deviation increase in definite intangible assets compared to an increase of 5.5 percent increase if each of those amounts would be subsumed under goodwill and assuming an unchanged goodwill coefficient because the true counterfactual is hard to observe. This result is consistent with amortized assets being less difficult and risky to audit than the annual impairment test of the goodwill. In sum, we find strong support for hypotheses 1 and 2.

[15] Coefficients are calculated the following: $(e^{0.420} – 1) * 0.0690 = 0.036$ | $(e^{0.331} – 1) * 0.0656 = 0.026$.

Table 2: Acquired intangible assets and audit fees

This table shows the results from OLS regressions examining whether acquired intangibles are associated with audit fees. The dependent variable, *Ln (Audit Fee)*, is the natural log of audit fees. All uneven columns (((1), (3), and (5)) explore the main effects of intangible assets. All even columns ((2), (4), and (6)) explore the moderation effect of audit risk on this association. Columns (1) and (2) explore the effects of acquired intangibles, while columns (3) and (4) explore the acquired intangibles, divided into definite and indefinite acquired intangibles. Columns (5) and (6) show the different associations for different intangible classes, within the acquired intangibles with definite and indefinite lifetimes. The definite and indefinite marketing intangibles serve as the reference group in columns (5) and (6). The acquired intangible variables (*Acquired_Int*, *Indef_Int*, *Def_Int)* and *Goodwill* are scaled by total assets, the different intangible classes (*Share Tech Indef, Share Contract Indef, Share Tech Def, Share Customer Def*, *Share Contract Def*, *Share Other Intangibles*) are scaled by total acquired intangible asset. Our proxy for audit risk *#AccLawsuits* is the change in the logarithm of one plus the number of accounting-related lawsuits that the firm is exposed to in 12 months after the filing of the annual report. Our coefficient of interest in the even columns is the interaction term. All variables are defined in Appendix A. All models include controls which are not reported for brevity, as well as industry (Fama-French 48) and year fixed effects. We interact all control variables in the even columns with *#AccLawsuits* to control for unobserved heterogeneity effects (deHaan et al. 2023). Standard errors are reported in parentheses below each coefficient estimate, with standard errors clustered by firm. The ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The period of observation is from 2009 to 2021 (totaling 18,931 observations in the uneven and 15,943 observations in the even columns).

Dependent Var.	*Ln (Audit Fee)*					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Acquired_Int$_{(i,t)}$	0.336***	0.329***				
	(0.096)	(0.102)				
# AccLawsuits$_{(i,t)}$ × *Acquired_Int*$_{(i,t)}$		0.126**				
		(0.052)				
Indef_Int$_{(i,t)}$			0.420***	0.350**	0.592***	0.524***
			(0.140)	(0.148)	(0.154)	(0.165)
# AccLawsuits$_{(i,t)}$ × *Indef_Int*$_{(i,t)}$				0.152**		0.211**
				(0.066)		(0.107)
Def_Int$_{(i,t)}$			0.331**	0.390***	0.148	0.232
			(0.137)	(0.146)	(0.155)	(0.165)
# AccLawsuits$_{(i,t)}$ × *Def_Int*$_{(i,t)}$				0.150*		0.118
				(0.088)		(0.106)
Goodwill$_{(i,t)}$	0.611***	0.586***	0.606***	0.575***	0.590***	0.563***
	(0.081)	(0.086)	(0.082)	(0.088)	(0.084)	(0.089)
# AccLawsuits$_{(i,t)}$ × *Goodwill*$_{(i,t)}$		-0.020		-0.023		-0.018
		(0.050)		(0.052)		(0.053)

(ctn. on next page)

Table 2: Acquired intangible assets and audit fees (ctn.)

Dependent Var.	*Ln (Audit Fee)*					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Indefinite Classes:						
Share Tech Indef					-0.096	-0.113
					(0.091)	(0.103)
# AccLawsuits$_{(i,t)}$ × *Share Tech Indef*						0.010
						(0.066)
Share Contract Indef					-0.099*	-0.107*
					(0.058)	(0.060)
# AccLawsuits$_{(i,t)}$ × *Share Contract Indef*						-0.040
						(0.052)
Definite Classes:						
Share Tech Def					0.139**	0.130**
					(0.059)	(0.061)
# AccLawsuits$_{(i,t)}$ × *Share Tech Def*						0.046
						(0.045)
Share Customer Def					0.081*	0.055
					(0.048)	(0.051)
# AccLawsuits$_{(i,t)}$ × *Share Customer Def*						-0.022
						(0.045)
Share Contract Def					-0.038	-0.035
					(0.063)	(0.065)
# AccLawsuits$_{(i,t)}$ × *Share Contract Def*						0.002
						(0.048)
Share Other Intangibles					0.045	0.048
					(0.068)	(0.072)
# AccLawsuits$_{(i,t)}$ × *Share Other Intangibles*						0.007
						(0.040)
# AccLawsuits$_{(i,t)}$		0.049		0.063		0.053
		(0.188)		(0.190)		(0.191)
Controls, Industry & Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,931	15,943	18,931	15,943	18,931	15,943

In columns (5) and (6), we observe that the coefficient of the indefinite intangibles further increases if we allow for the separate factor loadings of the different intangible classes. The share of tech indefinite acquired intangibles (e.g. in-process R&D) shows no statistically significant coefficients indicating that the overall discount of indefinite acquired intangibles does not significantly differ between the asset classes. Only for the share of indefinite contract acquired intangibles (e.g. broadcast rights) we find a negative coefficient, which just becomes statistically significant at the 10 percent level. Because the existence of these assets is easy to verify and some contracts and licenses are even traded at semi-liquid markets, their internal valuations can be benchmarked (Galasso et al. 2013; Bonacchi et al. 2015).

For intangible assets with a definite lifetime, we, in contrast, see that the coefficient becomes smaller and turns statistically non-significant of the overall amount of definite intangible assets, when using marketing intangibles with definite lifetime as our reference group. Moreover, for most other intangibles with a definite lifetime, we find no statistically significant markups. Nevertheless, we find positive and statistically significant mark-ups for definite technology intangibles (e.g. patents), which show with their very long lifetime strong similarities with indefinitely lived intangibles (Gilbert and Shapiro 1990). Additionally, the share of customer related intangibles with definite lifetimes show a small positive coefficient, which is also statistically significant at the 10 percent level in columns (5). Nevertheless, it remains far less expensive compared to goodwill. This result is highly interesting because the FASB discusses subsuming parts of the customer intangibles into the goodwill (FASB 2019) and some comment letters express concerns regarding the auditing of customer intangibles (Clor-Proell et al. 2022). Although the positive and significant coefficient provides evidence consistent with the claims that auditing of customer related intangibles can be challenging and risky compared to physical assets, results show that the markups are still much lower compared to the goodwill.

The interaction term with *#AccLawsuits* remains statistically non-significant for the different subclasses, which points to no major differences in the audit risk premium across the different classes. Overall, the results in columns (5) and (6) of Table 2 show that the effects of acquired intangibles on audit fees are heterogeneous regarding different economic lifetimes and classes. Regarding our control variables, which are only reported in the Online Appendix OA7 to facilitate the readability of our Table 2, our regressions show, in general, expected signs in line with prior literature (Zhang 2018; Hribar et al. 2014).

4.2 Difference-in-differences: CAM disclosure, audit fees and acquired intangibles

Finally, we turn to hypotheses 3 and investigate whether CAMs reduce audit risks, which in turn are associated with lower audit fees. We rely on the first-time public disclosures of

CAMs in 2019 and 2020 as a quasi-natural experiment. In 2019 and 2020, the PCAOB allowed auditors for the first time to publicly disclose client's accounting areas that they perceive as subjective, difficult, and complex to audit. Furthermore, the auditor discloses how it addressed the specific matter in the audit, which deters auditor-related lawsuits by highlighting that the auditor performed the required audit tasks. To validate the argument, we start by descriptively exploring the content and length of CAMs conditional on their topic of our firms' CAMs from Audit Analytics (12,446 CAM observations). See Appendix B for one example of an audit report with an intangible CAM and the description of how the auditor addressed the matter.

Table 3 therefore shows the frequency of CAMs on intangibles, goodwill, (initial) business combinations, tangible assets, as well as tax-related matters. Because business combination CAMs refer to the initial recognition of the business combination, whereas all other CAMs refer to the (carrying) net amounts of the respective topic, business combinations provide a meaningful benchmark for comparing the initial and the subsequent audit challenges of takeovers. Tangible CAM provide a meaningful benchmark for the audit challenges and the auditors' description characteristics of how they addressed the audit challenges in the CAM subject. Additionally, we report CAM characteristics for tax-related CAMs, which is a frequent CAM topic, yet it is less closely related to the firm's assets, to provide another more unrelated benchmark.

Table 3: CAM characteristics

This table shows the frequency of CAMs with different topics, the content, and length of the CAM section, in which the auditor describes how they addressed the critical audit matter for the universe of CAMs in our sample (12,446 different CAM observations). Because our sample firms might receive multiple CAMs within one year, the number of CAM observations differs from our number of firm years. This bigger sample yields a comprehensive picture of the population of all CAMs. Because we do not restrict our sample to observations for which we have hand-collected intangible assets and many firms receive multiple CAMs by their auditors, the number of observations of Table 4 differs from those in the other tables. *Intangible CAM* (*Goodwill CAM*, *Business Combination CAM*) refers to critical audit matters on intangibles (goodwill, business combination), as classified by the Audit Analytics' topic description. Because business combination CAMs refer to the initial recognition of the business combination, whereas all other CAMs refer to the (carrying) amounts of the respective topic, business combinations provide a meaningful benchmark for comparing the initial to the subsequent audit challenges of takeovers. *Tangible CAM* similarly refers to CAMs with respect to the carrying amount of tangible assets, as classified by the Audit Analytics' topic description. They provide a meaningful benchmark for the audit challenges and the auditors' description characteristics of how they addressed the audit challenges in the CAM subject. Additionally, we report CAM characteristics for tax-related CAMs (*Tax CAM*), which is a frequent CAM topic, yet it is less closely related to the firm's assets and take-over activities, to provide another more unrelated benchmark. *Use of Valuation Specialists* is an indicator variable which takes the value of one if the auditor highlights the use of valuation specialists or valuation experts in its description of how the auditor addressed the matter in the audit, and zero otherwise. Additionally, we report test results on the equality of proportions compared to intangible-related CAMs. *Length of How a Matter is Addressed* refers to the number of words, that the auditor uses in its audit report to describe how the CAM-related audit matter was addressed. Additionally, we report t-test results compared to Intangible CAMs. The ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

		CAM Frequency	**Use of Valuation Specialists**			**Length of How a Matter is Addressed**		
				Difference to (1)			Difference to (1)	
	Variable	N	Mean	Prob > |z|	Sig	Mean	Prob > |z|	Sig
(1)	Intangible CAM	521	0.521			193.13		
(2)	Goodwill CAM	1,425	0.520	0.517		200.02	0.112	
(3)	Business Combination CAM	1,353	0.545	0.339		185.67	0.015	**
(4)	Tangible CAM	1,248	0.192	0.000	***	163.87	0.000	***
(5)	Tax CAM	897	0.224	0.000	***	174.68	0.000	***

From Table 3, we see that intangible assets are a matter that is raised by the auditor in a CAM around half as frequent as tangible assets or a bit less than tax-related matters. Goodwill or the initial valuation of business combinations are more than double as often subject to CAMs. The lower frequency is inconsistent with the use of intangible CAMs in a generic way with boilerplate statements but speaks more to the auditor's careful and intentional use of intangible CAMs that is well suited to prevent audit risks with respect to the audit of intangible assets.

Looking into the texts, we find that the auditor highlights the use of valuation experts (internal) and valuation specialists (external) in around 52.015 percent of all intangible CAMs. This is 2.5 times as often compared to the valuation of tangible assets with tangible CAMs (only 19.15 percent) or tax-related CAMs (22.41 percent) and about the same compared to goodwill CAM (52.00 percent) but slightly less in CAMs on the initial business combinations (54.47 percent). This result on the use of valuation experts and specialists not only highlights the auditor's use of additional validation and confirmation of their work by specialists. Results also reveal that the auditors actively communicate the employment in their audit report, potentially to signal their substantial audit work. We also see that, with an average of about 193 words, the description of how the auditor addressed intangible-related matters is longer than the description on most other topics such as taxes (175 words) or tangible assets (164 words), again pointing to the auditor's intentionally signaling their substantial work to the public in the audit report.

Because the introduction of the CAM disclosures to all firms is unrelated to the economic fundamentals of any single firm, we argue that the introduction of CAMs can be used as a form of exogenous variation. Furthermore, the disclosure allows us to use the same firm before 2019 as its own control group in a difference-in-differences approach. We restrict our sample to the period from 2015 through 2020 to make sure that the firms before the first-time, intangible-related CAM disclosure remains a proper control.[1] Furthermore, we rely on firms that do not receive these CAMs to capture confounding time trends.

Before conducting a difference-in-differences test, we first need to test for the common trend in the association between acquired intangibles and audit fees in the pre-period for the difference-in-differences to work properly (Roberts and Whited 2013; Glaeser and Guay 2017; Armstrong et al. 2022). Figure 2 shows that there are no statistically significant differences in the associations between indefinite acquired intangibles and audit fees in any year before the first-time disclosure of CAMs. Only after the CAMs are also publicly disclosed we observe that the association between indefinite acquired intangibles and audit fees differs between those firms that receive an intangible-related CAM and those that receive other types of CAMs. The results from Figure 2 provides support for the common trend assumption.

[1] Our results remain qualitatively the same, if restrict our period to alternative time periods (2016-2020, 2017-2020). Moreover, we do not include the year 2021, because we are interested to investigate the effect of the introduction of CAMs on acquired intangible assets.

Figure 2: Common trend analysis of audit fees before and after CAM introduction

This graph illustrates the common trend analysis of the coefficient estimate for indefinite acquired intangibles (*CAM_int* × *Indef_Int*). The graph plots the coefficients on the interaction term before (2015-2018) and after (2019-2020) the introduction of CAMs. The upper and lower bars represent confidence intervals on the 5 and 95 percent levels. The confidence intervals are calculated based on clustered standard errors by firm. The dashed line indicates a theoretical coefficient of zero. The period of observation is from 2015 to 2020.

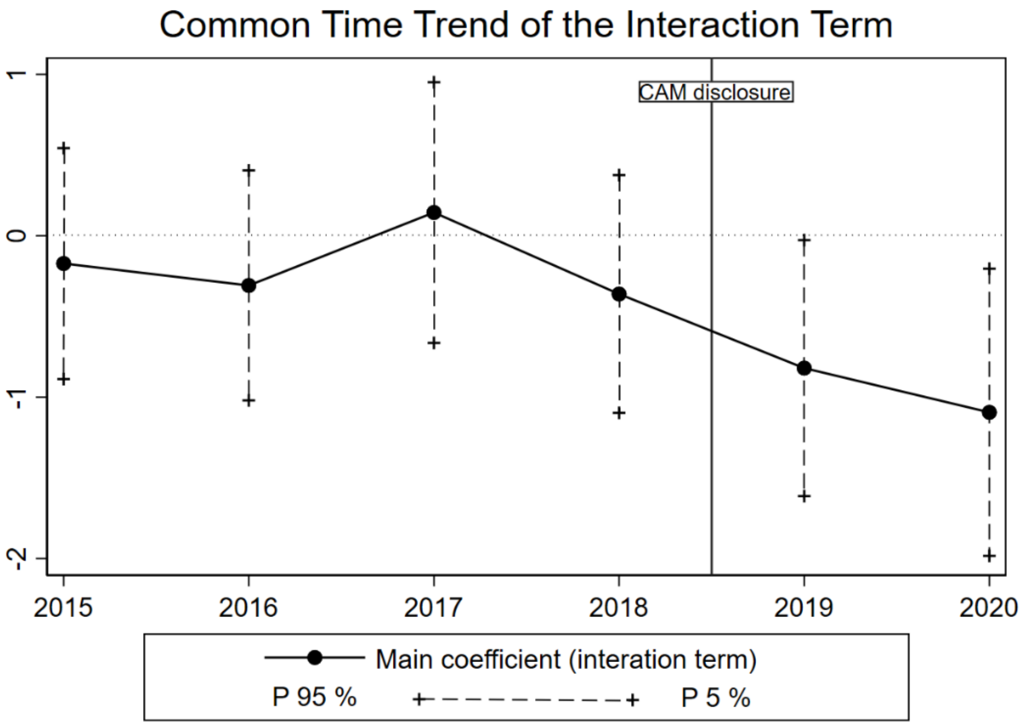


Table 4 shows the multivariate results of the difference-in-differences analysis of the coefficient of acquired intangible assets on audit fees in which the first difference (*CAM_int*) is whether a firm received an intangible-related CAM either for the year 2019 or 2020.[2] This variable is time-invariant and identifies treated firms. The second difference (*Post*) indicates whether a CAM is publicly disclosed, i.e. it takes the value of one for the years 2019 and 2020, and zero otherwise.

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[2] In Appendix OA9, we provide descriptive evidence on the occurrence of intangible CAMs in our sample as well as the determinants of intangible CAMs.

Table 4: Reduction of audit fees for risky intangibles through CAM disclosure

This table shows the results from examining the reduction in audit fees through CAM disclosure in a difference-in-differences design. *Post* is an indicator variable equal to one for the CAM period (2019-2020), and zero for the pre-period (2015-2018). *CAM_int* is an indicator variable equal to one when the firm receives a CAM for acquired intangibles in 2019 or 2020, and zero otherwise. Our coefficient of interest is the triple-interaction term. The dependent variable, *Ln (Audit Fee)*, is the natural log of audit fees. Column (1) addresses acquired intangibles, while column (2) addresses acquired intangibles, divided into definite and indefinite acquired intangibles. Because the groups in the triple interactions become very small, we refrain from reporting the division into lifetimes by classes, which constitutes column (3) in the other tables. The acquired intangible asset variables (*Acquired_Int*, *Def_Int*, *Indef_Int*) and *Goodwill* are scaled by total assets. All variables are defined in Appendix A. All models include controls, which are not reported for brevity, as well as industry (Fama-French 48) and year fixed effects. The main effect of *Post* gets subsumed under the year fixed effects and is consequently not reported separately. We interact all control variables with *CAM_int* to control for unobserved heterogeneity effects (deHaan et al. 2023). Standard errors are reported in parentheses below each coefficient estimate, with standard errors clustered by firm. The ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent Var.	*Ln (Audit Fee)*	
	(1)	*(2)*
Triple Interactions:		
Acquired $Int_{(i,t)} \times CAM\_int_{(i)} \times Post_{(t)}$	-0.345*	
	(0.188)	
$Indef\_Int_{(i,t)} \times CAM\_int_{(i)} \times Post_{(t)}$		-0.794***
		(0.283)
$Def\_Int_{(i,t)} \times CAM\_int_{(i)} \times Post_{(t)}$		-0.026
		(0.305)
Double Interactions:		
Acquired $Int_{(i,t)} \times Post_{(t)}$	0.125	
	(0.125)	
$Indef\_Int_{(i,t)} \times Post_{(t)}$		0.534**
		(0.229)
$Def\_Int_{(i,t)} \times Post_{(t)}$		-0.154
		(0.160)
Acquired $Int_{(i,t)} \times CAM\_int_{(i)}$	0.063	
	(0.265)	
$Indef\_Int_{(i,t)} \times CAM\_int_{(i)}$		-0.131
		(0.353)
$Def\_Int_{(i,t)} \times CAM\_int_{(i)}$		0.381
		(0.416)
$CAM\_int_{(i)} \times Post_{(t)}$	0.027	0.018
	(0.053)	(0.055)
Main Effects:		
$Acquired\_Int_{(i,t)}$	0.326**	
	(0.141)	
$Indef\_Int_{(i,t)}$		0.429*
		(0.223)
$Def\_Int_{(i,t)}$		0.296
		(0.199)
$CAM\_int_{(i)}$	-1.106*	-1.092*
	(0.628)	(0.635)
$Goodwill_{(i,t)}$	0.538***	0.550***
	(0.101)	(0.103)
Interacted Controls, Industry & Year FEs	Yes	Yes
Observations	8,399	8,399

In column (1) of Table 4, we investigate the relation amongst acquired intangibles. Interestingly, we find that the triple interaction of $Acquired\_Int_{(i,t)} \times CAM\_int_{(i)} \times Post_{(t)}$ shows a negative and statistically significant effect. This coefficient means that for the firms that receive an intangible-related CAM, the premium for acquired intangibles in the audit fee becomes lower by 0.345. Furthermore, we see that the base effect of $Acquired\_Int_{(i,t)}$ is positive for all firms irrespective of whether they receive an intangible-related CAM or not. Furthermore, all other main effects and their double interactions remain statistically non-significant at conventional levels. Because the double interactions, such as $Acquired\_Int_{(i,t)} \times CAM\_int_{(i)}$, capture the static difference between the treatment and the control group in this difference-in-differences test (Armstrong et al. 2022), these non-significant coefficients highlight that all static differences between the treatment and the control group are well captured by our control variables.[3] Because the base term of the *Post* indicator does not vary in the cross-section, it is subsumed under the year fixed effects and does not separately show up in the table. The results from column (1) of Table 4 show that with the disclosure of intangible-related CAMs, the audit effects of acquired intangibles and of goodwill diverge even more. Additional tests show that this result holds true even when considering the effects of goodwill-related CAMs. Overall, we learn from column (1) that the association between audit fees and intangibles becomes much weaker compared to that of goodwill once auditors are able to disclose intangible-related CAMs.

In column (2) of Table 4, we see a statistically high, negative triple-interaction effect for the indefinite acquired intangibles while the triple-interaction effect of the definite acquired intangibles is negative, yet statistically non-significant and much smaller in economic size. Furthermore, we see a positive double interaction effect of $Indef\_Int_{(i,t)} \times Post_{(t)}$, which shows

[3] Triple interactions frequently show non-significant double interactions (e.g., Reid et al. (2019), Table 3) because the treatment effect is captured by the fully interacted model. Only the remaining uncaptured effects, e.g. level differences between the treatment and control group or otherwise unexplained time trends, would show up in these double interactions (Greene 2019).

that the link between the indefinite acquired intangibles and audit fees becomes larger in the post-period for all firms, but the negative triple interaction tells us that this increase gets overcompensated for by those firms where the auditor publicly discloses an intangible-related CAM. Additional tests, again, show the differences in the audit effects between acquired intangibles and goodwill following the CAM disclosures. Furthermore, these differences are stronger for the indefinite acquired intangibles but for the definite acquired intangibles, the differences are already there even before the CAM disclosures.

Overall, the results in Table 4 provide empirical support for the evidence that acquired intangibles increase the firm's audit fees primarily through an increase in audit risk. Furthermore, we see that the public disclosure of intangible-related CAMs that arguably reduces the auditor's area-specific audit risk can reduce the premium for acquired intangibles in the audit fees. Thereby, acquired intangibles are related less to audit fees compared to goodwill.

4.3 Robustness tests

In this subsection, we investigate whether our results remain robust with regard to different specifications. First, one might argue that the disclosure of any CAM serves as a protection against potential audit risks, and hence, any CAM disclosure may lead to a decline in audit fees. In this case, our results from Table 4 are not necessarily driven by intangible-related CAMs, but by any type of CAMs. To alleviate this concern, we perform three different placebo tests in Table 5. We start by replicating Table 4 but use the tax-related CAMs instead of only intangible-related CAMs. In addition, we complement our model from Table 4 with additional interactions with tax-related CAMs to see whether our core results remain qualitatively unchanged. In a second placebo test in columns (5) through (8), we repeat the analyses but use goodwill-related CAMs as an alternative CAM measure. Lastly, we interact the goodwill-related CAMs not with the amounts of intangible assets, but with goodwill to investigate whether our results remain robust after including this additional explanatory interaction.

Table 5 shows that throughout all specifications, the additional placebo tests show weaker and mostly non-significant effects in statistical terms. At the same time, our initial results in columns (3), (4), (7) through (10) remain robust of including those alternative interactions. Only in column (6), we find weak interaction effects with indefinite intangible assets and goodwill CAMs, if we do not control for the effect of intangible CAMs. Nevertheless, the effect disappears once we properly include intangible CAMs and its interactions.

Table 5: Placebo tests on the audit fees effects for risky intangibles through CAM disclosure

This table shows the results from Placebo tests of Table 4 on the audit fee effects of CAM disclosure in a difference-in-differences design. All variables and specification are similar to those in Table 4. In columns (1) and (2) [(3) and (4)], we replace [complement] the triple interaction effect of intangible related CAMs, *CAM_int*, with an indicator variable for tax CAMs (*Tax CAM*) of firm i. In columns (5) through (8), we use goodwill-related CAMs (*Goodwill CAM*) as an alternative placebo variable and control for the effect of goodwill CAMs on the audit fee effects of goodwill in columns (9) and (10). All variables are defined in Appendix A. All models include interactions, main effects, and interacted controls variables (deHaan et al. 2023) similar to Table 4. Standard errors are reported in parentheses below each coefficient estimate, with standard errors clustered by firm. The ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*
	1st Placebo Test				2nd Placebo Test				3rd Placebo Test	
Triple Interactions:										
Acquired Int$_{(i,t)}$ $\times$ *CAM_int*$_{(i)}$ $\times$ *Post*$_{(t)}$			-0.288				-0.361*		-0.347*	
			(0.188)				(0.201)		(0.193)	
Indef_Int$_{(i,t)}$ $\times$ *CAM_int*$_{(i)}$ $\times$ *Post*$_{(t)}$				-0.688**				-0.754***		-0.760***
				(0.287)				(0.287)		(0.283)
Def_Int$_{(i,t)}$ $\times$ *CAM_int*$_{(i)}$ $\times$ *Post*$_{(t)}$				-0.004				-0.178		-0.085
				(0.304)				(0.310)		(0.310)
Placebo Variable: # CAMs$_{(i)}$										
Acquired Int$_{(i,t)}$ $\times$ *Tax CAM*$_{(i)}$ $\times$ *Post*$_{(t)}$	0.021		-0.073							
	(0.179)		(0.198)							
Indef_Int$_{(i,t)}$ $\times$ *Tax CAM*$_{(i)}$ $\times$ *Post*$_{(t)}$		0.105		-0.157						
		(0.273)		(0.311)						
Def_Int$_{(i,t)}$ $\times$ *Tax CAM*$_{(i)}$ $\times$ *Post*$_{(t)}$		0.059		0.186						
		(0.286)		(0.289)						
Placebo Variable: *Goodwill CAM* $_{(i)}$										
Acquired Int$_{(i,t)}$ $\times$ *Goodwill CAM*$_{(i)}$ $\times$ *Post*$_{(t)}$					-0.057		0.104			
					(0.180)		(0.199)			
Indef_Int$_{(i,t)}$ $\times$ *Goodwill CAM*$_{(i)}$ $\times$ *Post*$_{(t)}$						-0.395*		0.001		
						(0.235)		(0.222)		
Def_Int$_{(i,t)}$ $\times$ *Goodwill CAM*$_{(i)}$ $\times$ *Post*$_{(t)}$						0.360		0.425		
						(0.291)		(0.316)		
Goodwill$_{(i,t)}$ $\times$ *Goodwill CAM*$_{(i)}$ $\times$ *Post*$_{(t)}$									0.216	0.223
									(0.135)	(0.136)
Double Interactions, Main Effects, Interacted Controls, FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,399	8,399	8,399	8,399	8,399	8,399	8,399	8,399	8,399	8,399

Table 6: Robustness tests

This table shows the results from various alternative specifications of Table 2, columns (1) through (4) on the association of acquired intangibles and audit fees. Similar results for columns (5) and (6) of Table 2 are reported in the online Appendix OA7. Columns (1) through (4) of Table 6 uses robust regression design with a MM-estimator (e.g., Leone et al. (2019), Gassen and Veenman (2023)). In columns (5) through (8), we control for potential audit-firm effects (Audit-firm FE) and in columns (9) through (12), we exclude firms with zero acquired intangible asset. Columns (5) through (12) report results from estimating OLS regressions. The dependent variable, *Ln (Audit Fee)*, is the natural log of audit fees. Each block starts by addressing the acquired intangibles and continues by addressing the acquired intangibles, divided into definite and indefinite acquired intangibles. The acquired intangible variables (*Acquired_Int*, *Indef_Int*, *Def_Int*) and *Goodwill* are scaled by total assets. All variables are defined in Appendix A. Columns (1) through (4) include controls (models (5) through (12) interacted controls) which are not reported for brevity, as well as industry (Fama-French 48) and year fixed effects. Standard errors are reported in round parentheses below each coefficient estimate, with standard errors clustered by firm. The ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent Var.	*Ln (Audit Fee)*											
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*
$Acquired\_Int_{(i,t)}$	0.339***	0.328***			0.344***	0.343***			0.249**	0.217**		
	(0.096)	(0.103)			(0.093)	(0.100)			(0.099)	(0.106)		
$\# AccLawsuits_{(i,t)} \times$		0.075*				0.115**				0.125**		
$Acquired\_Int_{(i,t)}$		(0.039)				(0.052)				(0.059)		
$Indef\_Int_{(i,t)}$			0.421***	0.364**			0.420***	0.355**			0.353**	0.251*
			(0.140)	(0.149)			(0.140)	(0.149)			(0.144)	(0.151)
$\# AccLawsuits_{(i,t)} \times$				0.096*				0.149**				0.163**
$Indef\_Int_{(i,t)}$				(0.057)				(0.066)				(0.070)
$Def\_Int_{(i,t)}$			0.336**	0.368**			0.337***	0.400***			0.197	0.243*
			(0.139)	(0.150)			(0.129)	(0.138)			(0.138)	(0.147)
$\# AccLawsuits_{(i,t)} \times$				0.072				0.124				0.136
$Def\_Int_{(i,t)}$				(0.069)				(0.088)				(0.097)
$Goodwill_{(i,t)}$	0.576***	0.558***	0.570***	0.549***	0.598***	0.574***	0.594***	0.564***	0.475***	0.442***	0.477***	0.437***
	(0.085)	(0.091)	(0.086)	(0.092)	(0.078)	(0.083)	(0.079)	(0.084)	(0.083)	(0.088)	(0.083)	(0.089)
$\# AccLawsuits_{(i,t)} \times$		-0.006		-0.007		-0.014		-0.014		-0.020		-0.020
$Goodwill_{(i,t)}$		(0.037)		(0.039)		(0.050)		(0.051)		(0.053)		(0.055)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Audit-firm FE	No	No	No	No	Yes	Yes	Yes	Yes	No	No	No	No
Observations	18,931	15,943	18,931	15,943	18,930	15,942	18,930	15,942	14,241	11,952	14,241	11,952

Second, we investigate whether our baseline results in Table 2 are robust with respect to influential observations (Leone et al. 2019; Gassen and Veenman 2023). Inferences from OLS estimations might change because of the distorting effects of outliers, especially in audit fee regressions (Leone et al. 2019). Therefore, we reestimate columns (1) through (4) of Table 2 with a MM-estimator with a 90 percent Gaussian efficiency level.[42]

The results are reported in Table 6. Again, acquired intangibles are significantly associated with higher audit fees, but their pricing is smaller than that for goodwill. The moderation effect of audit risk becomes slightly weaker but remains statistically significant at conventional levels. A further division of intangibles among economic lifetimes and classes shows large heterogeneities with definite tech and indefinite marketing intangibles being significantly associated with audit fees. All columns remain consistent with the results in Table 2. With regard to the differences between acquired intangibles and goodwill, we find in additional but untabulated analyses that the audit of acquired intangible assets is significantly different from the goodwill position, especially for definite intangibles. Overall, the findings indicate that our results are not sensitive to specific outlier effects.

Third, we estimate our baseline results in Table 2 with audit-firm fixed effects in columns (5) through (8) of Table 6. Our previous results might be driven by auditor-specific categories or by the firm's selection of an auditor. Audit-firm fixed effects help mitigate those concerns. The results from columns (5) through (8) of Table 6, again, are in line with the previous results in Table 2. While goodwill has the largest coefficient due to the audit's complexity, the sizes of the coefficients of acquired intangible assets have not significantly changed. In additional tests, we find that acquired intangible assets, especially definite intangible assets, are significantly less expensive than goodwill regardless of the inclusion of audit-firm fixed effects. Therefore, our prior results are not sensitive to audit firm-specific effects.

[42] We do not report controls for columns (5) and (6) of Table 2 to enhance the readability of the table. We kindly refer to the online Appendix OA8 to see similar tests also for columns (5) and (6) of Table 2.

Fourth, we estimate our baseline results for non-zero intangible asset firm years only. Our previous sample also contains firm years with zero acquired intangible assets, i.e., firms that have not engaged in an M&A or acquired intangibles in singular transactions. Firms with acquired intangibles assets might be different to audit from firms with no acquired intangibles. Thus, we estimate our audit fee model within a subsample, put differently, a within intangible asset estimator of the effect. The results are reported in columns (9) through (12) of Table 6. The sizes of our significant coefficients are lower than in our previous tests. More importantly, however, our inferences remain the same, in other words, acquired intangible assets are cheaper to audit than goodwill.

An additional concern relates to the impact of critical audit matter dry runs carried out before the introduction (Center for Audit Quality 2018). In 2018, auditors began to identify client areas where they intended to issue CAMs but did not disclose this information to the public. Even without CAM disclosures in 2018, the dry runs may have affected the auditor-client relationship in terms of audit pricing and in many other dimensions. To mitigate the potential contaminating effects of the CAM dry runs, we exclude 2018 from our analyses in additional tests. The results of the additional tests show that all conclusions from our main tests remain qualitatively unchanged when 2018 is excluded. This gives us additional confidence that the 2018 dry run season is not driving our results.

Another concern relates to the possibility for non-accelerated filers to postpone the first disclosure of CAMs until 2020. Only accelerated-filers were required to disclose their CAMs in 2019, but non-accelerated-filers could do so voluntarily. The additional tests show that all conclusions from the tests remain unchanged if all non-accelerated filers are excluded from the sample, although the sample size in these tests becomes smaller.

5. Conclusion

In this paper we investigate the impact of acquired intangibles on audit fees and the issuance of intangible-related critical audit matters (CAMs) as a risk-reducing and thus audit fee decreasing device. Using a hand-collected sample of net amounts of acquired intangibles from 2009 to 2021, we find that acquired intangibles are positively associated with audit fees; however, our results support the expectations that they are easier to audit than goodwill. This finding holds true for both definite and indefinite acquired intangibles. In line with our predictions definite intangible assets are less expensive to audit than indefinite intangible assets. Nevertheless, we find a large heterogeneity among the different classes of acquired intangibles. Definite tech (patents and developed technology) and indefinite marketing (trademarks and brands) intangibles are significantly positively associated with audit fees, while many other classes remain insignificant. At the same time, acquired intangibles are frequently associated with receiving an intangible-related CAM, yet –in line with intuition- the probability is higher for indefinite intangible assets than for definite intangible assets. This evidence is consistent with acquired intangible assets are more associated with audit risk. Furthermore, our results regarding the introduction of intangible-related CAMs show that the premium on the acquired intangibles in the audit fees becomes lower after the public disclosure of intangible-related CAMs. First, this result points towards a higher mark up for audit risk by the auditor that might trigger additional procedures. Second, these results are also consistent with increasing the auditor's acceptable audit risk following from CAM disclosures. Because we are unable to follow firms many years after the CAM disclosures because they were disclosed only after 2019, it remains for subsequent studies to investigate whether the link between the acquired intangibles and firms' misstatements also increased after the CAM disclosures, that is, whether there is more audit risk.

Overall, these results extend the role of Critical Audit Matters (CAM) given the mixed findings in this growing body of literature (see Burke et al. 2023, Brasel et al. 2016; Brown et al. 2020; and Kachelmeier et al. 2020). Lastly, our study answers the recent calls from both academics (Clor-Proell et al. 2022) and standard setters (FASB and IASB) to separately investigate the roles of the amounts of acquired intangibles and the costs as well as the benefits of capitalizing them apart from goodwill.

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Appendix A: Variable definitions

Variable	Definition	Source
Dependent variables:		
Ln (Audit Fee)	Natural logarithm of audit fees.	Audit Analytics
Intangible asset variables:		
Acquired_Int	Net amount of acquired intangibles scaled by total assets.	Hand-collected database
Indef_Int	Net amount of acquired indefinite acquired intangibles scaled by total assets.	Hand-collected database
Share Marketing Indef	Net amount of acquired intangibles related to indefinite marketing scaled by net intangible assets.	Hand-collected database
Share Tech Indef	Net amount of acquired intangibles related to indefinite tech scaled by net intangible assets.	Hand-collected database
Share Contract Indef	Net amount of acquired intangibles related to indefinite contract scaled by net intangible assets.	Hand-collected database
Def_Int	Net amount of acquired definite intangibles scaled by total assets.	Hand-collected database
Share Tech Def	Net amount of acquired intangibles in definite tech class scaled by net intangible assets.	Hand-collected database
Share Marketing Def	Net amount of acquired intangibles in definite non-compete agreements and other marketing classes scaled by net intangible assets.	Hand-collected database
Share Customer Def	Net amount of acquired intangibles in customer class scaled by net intangible assets.	Hand-collected database
Share Contract Def	Net amount of acquired intangible in definite contract classes scaled by net intangible assets.	Hand-collected database
Share Other Intangibles	Net amount of acquired intangibles that are not allocated into one of the four specific categories. For instance, it contains commingled positions as well as artistic intangibles scaled by total assets.	Hand-collected database
Control variables:		
Intangible CAM (CAM_int)	Indicator variable equal to one if firm receives a critical audit matter for their acquired intangible positions, and zero otherwise.	Audit Analytics
Goodwill CAM	Indicator variable equal to one if firm receives a critical audit matter for their goodwill position, and zero otherwise.	Audit Analytics
Tax CAM	Indicator variable equal to one if firm receives a critical audit matter for their tax position, and zero otherwise	Audit Analytics
Goodwill	Net amount of goodwill scaled by total assets.	Compustat

Control variables (ctn.):

Size	Natural logarithm of total sales.	Compustat
Employees	Square root of the number of employees of the firm.	Compustat
ROA	Net income scaled by total assets.	Compustat
CashR	Cash and cash equivalents scaled by assets.	Compustat
Sales Growth	Change in total sales from prior to current period.	Compustat
Special Items	Special items scaled by total assets.	Compustat
InvRec	Inventory and receivables scaled by total assets.	Compustat
BTM	Book value of equity divided by market value of equity.	Compustat
CurrentR	Amount of current assets divided by current liabilities.	Compustat
Foreign	Amount of sales generated in foreign jurisdictions divided by total sales.	Compustat
Leverage	Sum of short-term debt and long-term debt scaled by total assets.	Compustat
Loss	Indicator variable equal to one if income before extraordinary items and discontinued operations is negative in the current or two previous years, and zero otherwise.	Compustat
Smooth	Indicator variable equal to one if firms' income is above the median among those firms with a positive in income, and zero otherwise.	Compustat
Restatement	Indicator variable equal to one if the firm restated their financial statements, zero otherwise.	Audit Analytics
Merger	Indicator variable equal to one if firm is engaged in a merger or acquisition, and zero otherwise.	Compustat
IPO	Indicator variable equal to one in the first year of reporting in Compustat, and zero otherwise.	Compustat
SEO	Indicator variable equal to one if the firm increased its shares outstanding by at least 10 percent, that is more than only by issuing employee shares, and zero otherwise.	Compustat
Business Segment	Square root of the number of business segments of the firm.	Compustat
NAF	Non-audit fees divided by audit fees.	Audit Analytics
Big_N	Indicator variable equal to one when the firm's auditor is a member of the Big 4, and zero otherwise.	Compustat
Busy Season	Indicator variable equal to one if firm's fiscal year end is in December, zero otherwise.	Compustat
Audit Opinion	Indicator variable equal to one if the firm receives a modified audit opinion, and zero otherwise.	Audit Analytics
Audit Timeliness	Natural logarithm of the number of calendar days from the fiscal year-end to the signature date of the auditor's report.	Audit Analytics
Tenure	Square root of years that the auditor is with the firm.	Compustat
Weak_404	Indicator variable that is equal to one if firm received an internal control weakness by the auditor, zero otherwise.	Audit Analytics
IndLeader_Fee	Indicator variable that is equal to one if auditor is an industry expert within the particular industry, and zero otherwise (see, e.g., Reichelt and Wang (2010)).	Audit Analytics
Litigation	Indicator variable equal to one for high litigation risk industries, and zero otherwise, as defined in Francis et al. (1994).	Compustat
Previous_Lawsuit	Indicator variable equal to one if the firm faced an accounting-related lawsuit in the last 12 months, zero otherwise.	Audit Analytics
# AccLawsuits	The change in the logarithm of the number of accounting-related lawsuits. It is measured by the change in the ongoing lawsuits in 12 months after the annual report had been published.	Audit Analytics
TV_Industry_Ind	Indicator variable that is equal to one if firm is in the following Standard classification codes: 4841, 4832; and zero otherwise.	Compustat

Appendix B: Example of a critical audit matter (CAM) disclosure about acquired intangibles

Example of Walmart Incorporated (2021, page 52):

Valuation of Indefinite-Lived Intangible Assets

Description of the Matter

At January 31, 2021, the Company has $4.9 billion of indefinite-lived intangible assets, which primarily consist of acquired tradenames. As disclosed in Notes 1, 8 and 12 to the Consolidated Financial Statements, these assets are evaluated for impairment at least annually using valuation techniques to estimate fair value. These fair value estimates are sensitive to certain significant assumptions including revenue growth rates, discount rates, and royalty rates.

Auditing management's annual indefinite-lived intangible assets impairment tests was complex and highly judgmental due to the significant measurement uncertainty in determining the fair values of the indefinite-lived intangibles. For example, the fair value estimates are sensitive to significant assumptions identified above that are affected by future market or economic conditions.

How We Addressed the Matter in Our Audit

We obtained an understanding, evaluated the design and tested the operating effectiveness of controls over the Company's indefinite-lived intangible asset impairment review process. Our procedures included, among others, testing controls over management's review of the significant assumptions described above used to estimate the fair values of the indefinite-lived intangible assets.

To test the estimated fair values of the indefinite-lived intangible assets, we performed audit procedures that included, among others, assessing methodologies used to determine the fair value, testing the significant assumptions discussed above and testing the completeness and accuracy of the underlying data used by the Company. For example, we evaluated management's forecasted revenue growth rates used in the fair value estimates by comparing those assumptions to the historical results of the Company and current industry, market and economic forecasts. We involved a valuation specialist to assist in evaluating the valuation methodologies and the significant assumptions such as discount rates and royalty rates. Additionally, we performed sensitivity analyses of significant assumptions to evaluate the effect on the fair value estimates of the indefinite-lived intangible assets.

Online Appendix OA1: Example of a lawsuit, which refers to the lack of relevant critical audit matter (CAM)

This Appendix OA1 provides an example of a lawsuit against an audit firm, KPMG, for, among other things, the lack of issuing a relevant critical audit matter (CAM). Thereby, the relevant passage from point 109 is highlighted in bold and italic letters by the auditors and is given a frame to be identified more easily. Source: https://storage.courtlistener.com/recap/gov.uscourts.cand.410878/gov.uscourts.cand.410878.1.0.pdf. This example is also mentioned by WSJ (2023) to illustrate the link between CAMs and litigation risk.

(…)

109. The 2022 Annual Report included an audit report signed by the Company's auditor, KPMG, reflecting the results of its audit of SVB's 2021 and 2022 financials. KPMG certified that "the consolidated financial statements referred to above present fairly, in all material respects, the financial position of the Company as of December 31, 2021 and 2022, and the results of its operations and its cash flows for each of the years in the three-year period ended December 31, 2022, in conformity with U.S. generally accepted accounting principles."

Even though SVB's deposits began to decline in 2022, falling $25 billion during the final nine months of 2022 and reducing SVB's liquidity, KPMG did not identify risks associated with SVB's declining deposits or SVB's ability to hold debt securities to maturity in its report.

Additionally, KPMG's audit report was silent as to whether—pursuant to Public Company Accounting Oversight Board AS 2415—there was "substantial doubt about [SVB's] ability to continue as a going concern for a reasonable period of time."

Online Appendix OA2: Types of acquired intangible assets

Online Appendix OA2 provides an explanation of the different lifetimes and classes of acquired intangible assets. Both the FASB and the IASB specify five different classes of intangibles in their frameworks: *tech*, *customer*, *contract*, *marketing*, and *artistic*.[43] *Tech* acquired intangibles mainly cover patents, in-process R&D, developed technologies, and software but also trade secrets, such as formulas and recipes. Auditors can easily verify the existence of patents and software as they are contractible, but their valuations can be challenging (Hall et al. 2005; Bena and Li 2014). The patents also lack a proper external benchmark for valuation because, by their nature, they are not traded on a liquid market and are often very specific. Furthermore, the valuation of patents requires both highly sophisticated technical knowledge as well as a good understanding of the firm's business model to quantify their economic benefits. Consequently, tech acquired intangibles require valuation experts that could increase the costs of an audit. Furthermore, valuations of patents and other tech intangibles involve a high level of managerial discretion.

Customer acquired intangibles cover customer lists and relationships but also order backlog. Most customer acquired intangibles closely relate to the firm's business activities, which makes it hard to disentangle their values from the overall goodwill. Furthermore, their valuation involves a large degree of subjectivity due industry specific characteristics such as varying switching costs (Dikolli et al. 2007). Consequently, auditors can face higher risk regarding those assets. Nevertheless, there are well-established procedures to estimate a client's value that auditors can compare to other firms. Consequently, customer acquired intangibles might show a better auditability compared to goodwill.

[43] Artistic acquired intangibles, such as performance events, literary works, musical works, and pictures as well as television programs are the rarest class of intangibles. They are clustered in very few firms in the entertainment industry and their valuation requires greater industry expertise. Because artistic acquired intangibles are very rare in our dataset, we do not separately investigate them but subsume them into other intangibles.

Contract acquired intangibles cover all sorts of tradable contracts, such as licensing agreements, service contracts, lease agreements, franchise agreements, broadcast rights, or employment contracts as well as use rights, such as drilling rights or water rights. Some of these rights show definite lifetimes because the contracts expire, while other contracts such as FCC licenses can have indefinite lifetimes. Similar to patents, the existence of a contract acquired intangibles is easily verifiable. Some of these intangibles, such as broadcasting or air landing rights, also possess market benchmarks for their valuations (Olbrich et al. 2009); while others, such as franchise agreements, are closely tied to the valuation of goodwill (Bonacchi et al. 2015). Consequently, contract acquired intangibles require less effort by the auditor and also possess lower levels of audit risk than goodwill.

Marketing acquired intangibles cover non-compete agreements, newspaper mastheads, internet domain names, as well as trademarks, tradenames, and brands. These acquired intangibles are characterized by a very close link to the firm's business activities and are, consequently, hard to differentiate from goodwill. Yet, some internally generated brands can have substantial value for investors (Barth et al. 1998; Vitorino 2014). Because most of them have an indefinite lifetime, these assets also require an annual impairment test by the auditor. Consequently, marketing acquired intangibles behave similarly to a firm's goodwill. Nevertheless, some of them possess valuation benchmarks from similar transactions and can even be pledged as collateral in a loan contract. Thereby, a bank can also provide assurance of reliability to some marketing acquired intangibles that reduces the underlying audit effort.

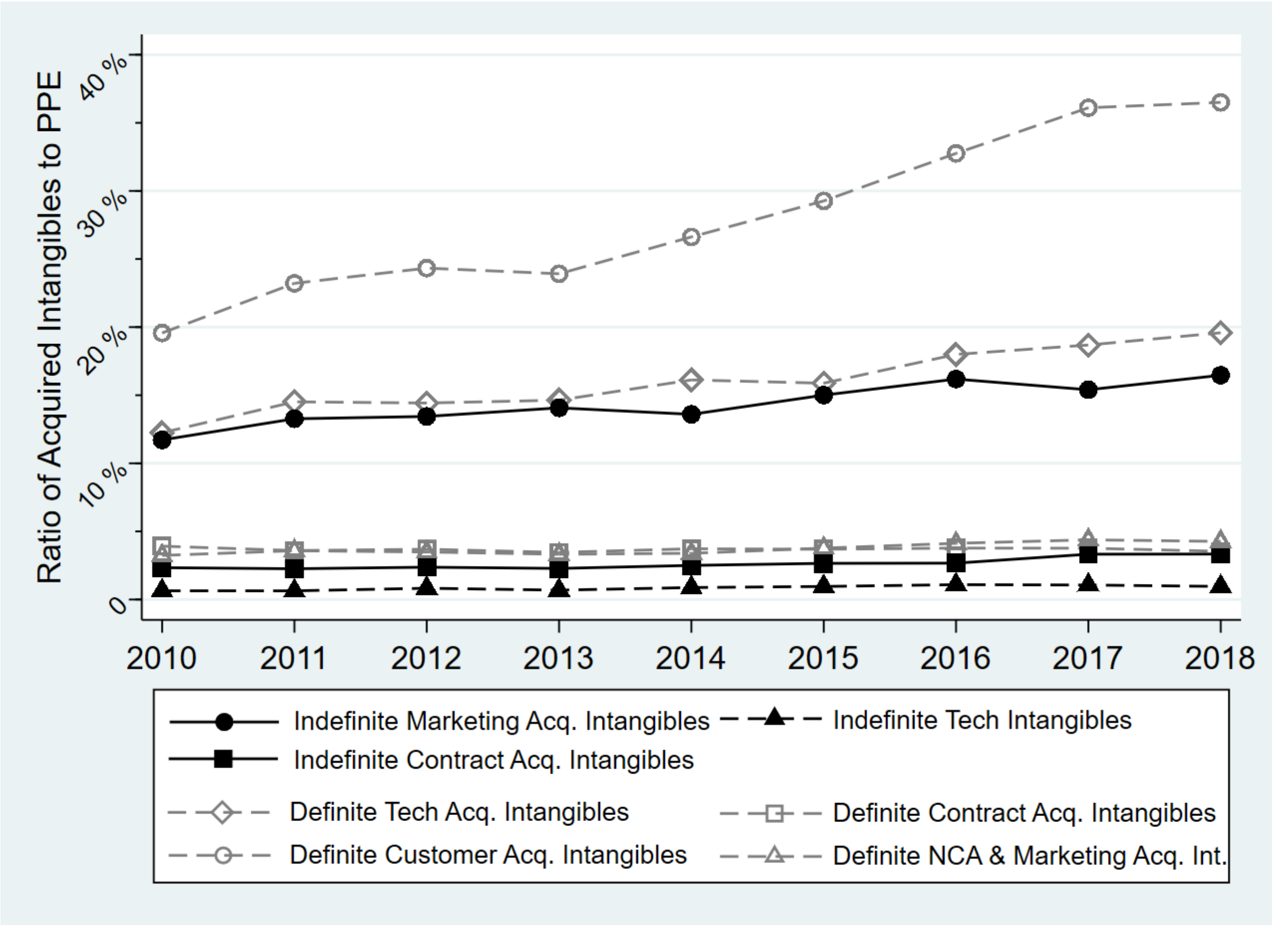
To illustrate the importance of each acquired intangible class, Online Appendix OA3 highlights the distribution of the different classes of acquired intangibles over time in relation to the amount of property, plant, and equipment (PPE). It shows that the acquired intangible classes develop differently over time. While all classes show a similar magnitude in the beginning of our sample period, Online Appendix OA3 shows a fast increase in customer intangibles at the beginning, which becomes flatter towards the end of our sample period. Since

2010, there has been a substantial increase in customer acquired intangibles that further accelerates towards the end of our sample period. Thereby, those acquired intangibles are the largest group, which is consistent with recent evidence that it has become the most prominent intangible asset in an acquisition (Beneish et al. 2022). Tech acquired intangibles show a smooth and steady increase in their economic magnitude and become the second most important group during the years 2016 through 2018. In contrast to the other three acquired intangible classes, contract acquired intangibles show hardly any increase during our sample period. Nevertheless, when compared to the firm's PPE, which we use for scaling in Figure 1 of the manuscript and Online Appendix OA3, we find that each of the different classes appear economically relevant to the firm.

Overall, the different classes of acquired intangibles show very different degrees of verifiability of and discretion in valuations. Most classes are fairly easy to verify, but their valuations partially require the expertise of specialists in terms of industry or technological knowledge. Furthermore, some of the acquired intangible classes are closely tied to the firm's business model and are, consequently, difficult to differentiate from goodwill.

Online Appendix OA3: Growth of different acquired intangibles in relation to property, plant & equipment

This graph illustrates the growth of different acquired intangible classes divided into definite and indefinite acquired intangibles (indefinite marketing, indefinite tech, indefinite contract, definite tech, definite marketing, definite customer, definite contract) in relation to property & plant, and equipment (PPE) over time (2010-2018).



Online Appendix OA4: Examples of intangible-related lawsuits

Online Appendix OA4 provides three distinct examples of accounting related lawsuits that center around the measurement of intangible assets.

1. Mordy v. KLX Inc et al (Case start date: 2016-01-06; Case end date: 2017-02-07)

According to the complaint, KLX allegedly materially misrepresented the value of KLX's assets. More specifically, KLX allegedly misrepresented the value of the identifiable intangible assets and goodwill associated with its Energy Services Group, as well as its policies and methodology related to the calculation of risk, goodwill, and asset impairment.

2. Margolis v. Fly Leasing Limited et al (Case start date: 2016-03-25; Case end date: 2016-10-07)

On March 25, 2016, Gerald Margolis filed a putative class action lawsuit in the United States District Court for the Southern District of New York, asserting that Fly Leasing Limited, Colm Barrington (our Chief Executive Officer), and Gary Dales (our Chief Financial Officer) violated Sections 10(b) and 20(a) of the Securities Exchange Act of 1934 and Rule 10b-5 promulgated thereunder by making materially false and misleading statements regarding the Company's business, operational and compliance policies, particularly concerning our accounting with respect to intangible assets and liabilities for aircraft acquired with in-place leases. The complaint seeks an unspecified amount of monetary damages on behalf of the putative class and an award of attorney's fees, expert fees and other costs. The case was voluntarily dismissed on October 7, 2016.

3. Oregon Laborers Employers Pension Trust Fund et al v. Maxar Technologies Inc et al (Case start date: 2019-01-14)

Plaintiffs allege that defendants violated Sections 10(b) and 20(a) of the Securities Exchange Act of 1934 (the Exchange Act) and Rule 10b-5 promulgated thereunder. According to the complaint, throughout the Class Period, Defendants made materially false and misleading statements regarding the Company’s business, operational and compliance policies. Specifically, Defendants made false and/or misleading statements and/or failed to disclose that: (i) Maxar improperly inflated the value of its intangible assets, among other accounting improprieties; (ii) Maxar’s highly-valued WorldView-4 was equipped with CMGs that were faulty and/or ill-suited for their designed and intended purpose; and (iii) as a result, Maxar’s public statements were materially false and misleading at all relevant times.

Online Appendix OA5: Example of acquired intangible asset disclosures

Online Appendix OA5 provides an example of how the break-up of acquired intangible assets is displayed on firms' financial statements. The example comes from the 2018 annual statement of Amazon Inc. about the intangible asset position of Fiscal Year 2017 (page 53).

Intangible Assets

Acquired intangible assets, included within "Other assets" on our consolidated balance sheets, consist of the following (in millions):

	2017		
	Acquired Intangibles, Gross (1)	Accumulated Amortization (1)	Acquired Intangibles, Net
Marketing-related	$ 2,486	$ (418)	$ 2,068
Contract-based	1,013	(213)	800
Technology- and content-based	640	(252)	388
Customer-related	283	(168)	115
Acquired intangibles (2)	$ 4,422	$ (1,051)	$ 3,371

(1) Excludes the original cost and accumulated amortization of fully-amortized intangibles.
(2) Intangible assets have estimated useful lives of between one and twenty-five years.

Online Appendix OA6: Sample compositions and descriptive statistics

Online Appendix OA6 provides the descriptive statistics for the sample distribution and all intangible asset variables used in this study. Panel A presents the industry composition of our sample. We define the industries by using the Fama-French 12 industry classifications (excluding the financial industry). Panel B presents the descriptive statistics for the acquired intangible variables. All amounts are denoted in US-$ million. The definitions of the variables can be found in Appendix A.

Panel A: Sample Composition

Industry	*N*	*Firms*	*Percentage*
Nondurables	1,368	182	7.23%
Durables	677	75	3.58%
Manufacturing	2,389	268	12.62%
Energy	974	130	5.15%
Chemical	764	89	4.04%
Equipment	3,761	480	19.87%
Telephone	799	98	4.22%
Utilities	513	54	2.71%
Shops	2,550	328	13.47%
Health	2,502	342	13.22%
Service	2,634	312	13.91%
Sum	18,931	2,358	100%

Panel B: Descriptive statistics on acquired intangible assets (in US-$ million)

Variables	*Mean*	*SD*	*Median*	*p75*	*p90*	*p99*
Acquired_Int	626.85	2,200.57	40.78	279.72	1,103.76	17,000.00
Indef_Int	209.06	927.61	0.00	30.12	284.30	7,660.00
Marketing Indef	*99.38*	*407.19*	*0.00*	*7.30*	*155.30*	*3,067.40*
Tech Indef	*6.39*	*40.24*	*0.00*	*0.00*	*0.00*	*347.20*
Contract Indef	*32.16*	*223.38*	*0.00*	*0.00*	*0.00*	*2,053.14*
Def_Int	362.07	1,222.72	21.07	166.05	687.30	9,467.00
Tech Def	*81.46*	*365.75*	*0.00*	*10.86*	*90.08*	*2,906.12*
Marketing Def	*17.32*	*73.07*	*0.00*	*1.90*	*22.20*	*564.10*
Customer Def	*115.72*	*361.50*	*0.88*	*52.95*	*257.00*	*2,591.10*
Contract Def	*22.46*	*103.96*	*0.00*	*0.00*	*17.32*	*802.00*
Goodwill	1,399.40	5,360.09	101.64	743.65	2,910.70	24,521.50

Online Appendix OA7: Main results with control variables

Online Appendix OA7 provides the regression coefficients and predicted signs from the literature (Hribar et al. 2014 (HR); Zhang 2018 (ZH)) for all control variables of Table 2, columns (1) and (2).

Dependent Var.		*Ln (Audit Fee)*	
	Projected Sign	*(1)*	*(2)*
Main Variables of Interest		See columns (1) and (2) of Table 2	
Full set of control variables			
Size		0.394***	0.398***
	+	(0.012)	(0.012)
# AccLawsuits$_{(i,t)}$ ×Size	(ZH)		-0.005
			(0.010)
Employees		0.068***	0.070***
	+	(0.008)	(0.008)
# AccLawsuits$_{(i,t)}$ ×Employees	(HR)		0.001
			(0.004)
ROA		-0.354***	-0.354***
	-	(0.063)	(0.063)
*# AccLawsuits$_{(i,t)}$ ×*ROA	(ZH)		0.032
			(0.067)
CashR		0.440***	0.450***
	+	(0.083)	(0.082)
# AccLawsuits$_{(i,t)}$ ×CashR	ZH		0.007
			(0.056)
Sales Growth		-0.108***	-0.110***
	-	(0.014)	(0.015)
# AccLawsuits$_{(i,t)}$ × Sales Growth	(ZH)		-0.010
			(0.023)
Special Items		-0.044	-0.012
	+	(0.117)	(0.117)
# AccLawsuits$_{(i,t)}$ × Special Items	(ZH)		0.303
			(0.190)
InvRec		-0.422***	-0.427***
	+	(0.088)	(0.089)
# AccLawsuits$_{(i,t)}$ × InvRec	(HR)		-0.019
			(0.048)
BTM		0.011	0.010
	-/ ?	(0.016)	(0.016)
# AccLawsuits$_{(i,t)}$ × BTM	(HR)		0.003
			(0.019)
CurrentR		0.004	0.004
	-	(0.006)	(0.006)
# AccLawsuits$_{(i,t)}$ × CurrentR	(HR)		0.009*
			(0.005)
Foreign		1.466***	1.480***
	+	(0.147)	(0.147)
# AccLawsuits$_{(i,t)}$ × Foreign	(HR)		-0.211**
			(0.099)

Online Appendix OA7 (ctn.)

Dependent Var.		*Ln (Audit Fee)*	
	Projected Sign	*(1)*	*(2)*
Leverage		0.130***	0.129***
	+	(0.049)	(0.049)
# AccLawsuits$_{(i,t)}$ × *Leverage*	(HR; ZH)		0.010
			(0.038)
Loss		0.108***	0.111***
	+	(0.017)	(0.017)
# AccLawsuits$_{(i,t)}$ × Loss	(HR; ZH)		-0.034*
			(0.019)
Smooth		-0.106***	-0.107***
		(0.016)	(0.016)
# AccLawsuits$_{(i,t)}$ × Smooth	-		-0.009
			(0.018)
Restatement		0.020	0.020
	+	(0.017)	(0.017)
# AccLawsuits$_{(i,t)}$ × *Restatement*	(ZH)		-0.075**
			(0.035)
Merger		0.106***	0.107***
	+	(0.014)	(0.014)
# AccLawsuits$_{(i,t)}$ ×Merger	(HR; ZH)		0.019
			(0.015)
IPO		0.291***	0.289***
	+	(0.051)	(0.053)
# AccLawsuits$_{(i,t)}$ × IPO	(HR; ZH)		-0.070
			(0.132)
SEO		0.118***	0.118***
	+	(0.016)	(0.016)
# AccLawsuits$_{(i,t)}$ × SEO	(HR; ZH)		0.029
			(0.030)
Business Segment		0.051***	0.050***
	+	(0.011)	(0.011)
# AccLawsuits$_{(i,t)}$ × *Business Segment*	(HR, ZH)		-0.003
			(0.006)
NAF		-0.231***	-0.227***
		(0.036)	(0.036)
# AccLawsuits$_{(i,t)}$ × *NAF*	-		-0.006
			(0.028)
Big_N		0.530***	0.528***
	+	(0.030)	(0.030)
# AccLawsuits$_{(i,t)}$ × *Big_N*	(HR)		0.045**
			(0.022)
Busy Season		0.072***	0.071***
	+	(0.022)	(0.023)
# AccLawsuits$_{(i,t)}$ ×*Busy Season*	(HR; ZH)		0.012
			(0.014)

Online Appendix OA7 (ctn.)

Dependent Var.		*Ln (Audit Fee)*	
	Projected Sign	*(1)*	*(2)*
Audit Opinion		0.044***	0.044***
	+	(0.013)	(0.013)
# AccLawsuits$_{(i,t)}$ × Audit Opinion	(HR; ZH)		-0.010
			(0.016)
Audit Timeliness		0.053	0.048
	?	(0.049)	(0.049)
# AccLawsuits$_{(i,t)}$ ×Audit Timeliness			-0.018
			(0.036)
Tenure		0.004	0.004
	+/?	(0.008)	(0.008)
# AccLawsuits$_{(i,t)}$ × Tenure	(HR)		-0.001
			(0.006)
Weak_404		0.247***	0.252***
	+	(0.029)	(0.029)
# AccLawsuits$_{(i,t)}$ × Weak_404			-0.035
			(0.039)
IndLeader_Fee		0.079***	0.080***
	+	(0.018)	(0.018)
# AccLawsuits$_{(i,t)}$ × IndLeader_Fee	(HR)		0.004
			(0.013)
TV_Industry_Ind		-0.418***	-0.407***
	-	(0.088)	(0.086)
# AccLawsuits$_{(i,t)}$ × TV_Industry_Ind			-0.048*
			(0.029)
Previous_Lawsuit		0.080***	
		(0.021)	
Litigation	+	-0.039	
	(HR)	(0.046)	
# AccLawsuits$_{(i,t)}$			0.049
			(0.188)
Industry & Year FE		Yes	Yes
Observations		18,931	15,943

HR: from Hribar et al. (2014), ZH: from Zhang (2018)

Online Appendix OA8: Robustness tests using robust regressions

This table shows the results from various alternative specifications of Table 2, columns (5) through (6) on the association of acquired intangibles and audit fees. It uses robust regression design with a MM-estimator in columns (1) and (2), audit-firm effects in columns (3) and (4), and we exclude firms with zero acquired intangible asset in columns (5) and (6). Columns (3) through (6) report results from estimating OLS regressions. The dependent variable, Ln (Audit Fee), is the natural log of audit fees. The acquired intangible variables and *Goodwill* are scaled by total assets, the shares of the different intangible classes (*Indef_Tech*, *Indef_Contract*, *Def_Tech*, *Def_Customer*, *Def_Contract*, *Other*) by total acquired intangible assets. Our proxy for audit risk *#AccLawsuits* is the change in the logarithm of one plus the number of accounting-related lawsuits that the firm is exposed to in 12 months after the filing of the annual report. Our coefficient of interest in the even columns is the interaction term. All variables are defined in Appendix A. Columns (1) through (4) include controls (models (5) through (12) interacted controls) which are not reported for brevity, as well as industry (Fama-French 48) and year fixed effects. Standard errors are reported in round parentheses below each coefficient estimate, with standard errors clustered by firm. The ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent Var.	*Ln (Audit Fee)*					
	Robust Regressions		*With Auditor FEs*		*Exclude zero intangible firms*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Indef_Int$_{(i,t)}$	0.603***	0.553***	0.508***	0.503***	0.373**	0.265
	(0.152)	(0.163)	(0.164)	(0.164)	(0.155)	(0.164)
# AccLawsuits$_{(i,t)}$ × *Indef_Int*$_{(i,t)}$		0.089		0.222**		0.185*
		(0.110)		(0.106)		(0.112)
Def_Int$_{(i,t)}$	0.199	0.255	0.212	0.248	0.217	0.288*
	(0.158)	(0.171)	(0.156)	(0.157)	(0.153)	(0.163)
# AccLawsuits$_{(i,t)}$ × *Def_Int*$_{(i,t)}$		0.017		0.093		0.120
		(0.110)		(0.107)		(0.107)
Goodwill$_{(i,t)}$	0.551***	0.520***	0.568***	0.561***	0.438***	0.395***
# AccLawsuits$_{(i,t)}$ ×	(0.087)	(0.093)	(0.085)	(0.085)	(0.086)	(0.092)
Goodwill$_{(i,t)}$		-0.013		-0.011		-0.023
		(0.059)		(0.052)		(0.058)
Indefinite Classes:						
Share Tech Indef	-0.163*	-0.163*	-0.081	-0.068	0.103	0.073
	(0.084)	(0.097)	(0.102)	(0.102)	(0.109)	(0.120)
# AccLawsuits$_{(i,t)}$ × *Share Tech Indef*		-0.007		0.004		0.014
		(0.052)		(0.068)		(0.074)
Share Contract Indef	-0.123**	-0.138**	-0.089	-0.097	-0.156***	-0.173***
	(0.062)	(0.064)	(0.060)	(0.059)	(0.060)	(0.062)
# AccLawsuits$_{(i,t)}$ × *Share Contract Indef*		0.011		-0.052		-0.039
		(0.053)		(0.052)		(0.053)
Definite Classes:						
Share Tech Def	0.147**	0.146**	0.133**	0.145**	0.093	0.062
	(0.058)	(0.061)	(0.060)	(0.060)	(0.063)	(0.066)
# AccLawsuits$_{(i,t)}$ × *Share Tech Def*		0.068		0.046		0.028
		(0.048)		(0.044)		(0.051)
Share Customer Def	0.040	0.025	0.051	0.036	-0.063	-0.096*
	(0.047)	(0.050)	(0.049)	(0.049)	(0.051)	(0.054)
# AccLawsuits$_{(i,t)}$ × *Share Customer Def*		-0.015		-0.026		-0.037
		(0.042)		(0.044)		(0.047)
Share Contract Def	-0.066	-0.059	-0.012	-0.017	-0.155**	-0.162**
	(0.068)	(0.071)	(0.063)	(0.063)	(0.072)	(0.076)
# AccLawsuits$_{(i,t)}$ × *Share Contract Def*		0.026		-0.007		-0.015
		(0.057)		(0.048)		(0.054)
Share Other Intangibles	0.080	0.089	0.054	0.053	-0.077	-0.087
	(0.063)	(0.066)	(0.071)	(0.072)	(0.071)	(0.075)
# AccLawsuits$_{(i,t)}$ × *Share Other Intangibles*		0.028		0.004		0.001
		(0.035)		(0.041)		(0.043)
# AccLawsuits$_{(i,t)}$		0.134		0.103		0.116
		(0.187)		(0.190)		(0.193)
Controls, Industry & Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Auditor FEs	No	No	Yes	Yes	No	No
Observations	18,931	15,943	15,942	15,942	14,241	11,952

Online Appendix OA9: Acquired intangibles and their related critical audit matter (CAM)

This table shows descriptive statistics from our subsample analysis investigating, which firms receive intangible-related critical audit matters (CAM). Panel A reports descriptive statistics of our dependent and independent variables from our sample. Panel B presents the industry composition of our restricted sample, the issuance of CAMs, intangible-related CAMs, and goodwill-related CAMs. The period of observation is from 2019 until 2021 (totaling 3,578 observations).

Panel A: Descriptive statistics of subsample (N = 3,578 firm years)

Variables	*Mean*	*SD*	*P25*	*Median*	*p75*	*p90*	*p95*
Intangible CAM	0.094	0.291	0	0	0	0	1
Goodwill CAM	0.194	0.395	0	0	0	1	1
Size	6.876	2.393	5.722	7.231	8.423	9.491	10.026
Age	3.108	0.720	2.708	3.258	3.611	4.007	4.060
Business Segment	1.898	0.815	1.414	1.732	2.449	3.162	3.464
BTM	0.437	0.594	0.145	0.331	0.625	1.016	1.428
Leverage	0.517	0.277	0.330	0.493	0.657	0.842	1.002
Merger	0.409	0.492	0	0	1	1	1
SEO	0.134	0.340	0	0	0	1	1
Smooth	0.435	0.496	0	0	1	1	1
Previous Lawsuit	0.094	0.292	0	0	0	0	1
Loss	0.503	0.500	0	1	1	1	1
Restatement	0.057	0.232	0	0	0	0	1
Big N	0.766	0.423	1	1	1	1	1
Tenure	3.765	1.389	2.646	3.873	4.690	5.568	6.325
Audit Timeliness	4.056	0.238	3.932	4.043	4.159	4.344	4.489
Weak_404	0.056	0.231	0	0	0	0	1
Litigation	0.367	0.482	0	0	1	1	1
A Filer	0.898	0.302	1	1	1	1	1

Panel B: Descriptive evidence of CAMs, intangible-related CAMs, and goodwill-related CAMs

Industries	*N*	*Received any CAM*	*Received an Intangible CAM*	*Received a Goodwill CAM*
Nondurables	274	197	69	60
Durables	129	96	10	33
Manufacturing	455	380	50	158
Energy	121	97	6	10
Chemical	152	130	23	54
Equipment	697	536	35	97
Telephone	140	109	33	39
Utilities	59	53	4	4
Shops	509	351	40	97
Health	565	412	41	49
Service	477	398	24	92
Sum	3,578	2,759	335	693

Panel C: Acquired intangibles and the probability of receiving a critical audit matter (CAM)

This table, Panel C, shows the results of examining whether acquired intangibles are associated with receiving a critical audit matter (CAM) about acquired intangibles and goodwill. It shows results of our logit estimation of equation (2). The dependent variable, *Intangible CAM*, is an indicator variable equal to one when receiving a CAM about acquired intangibles, and zero otherwise. Column (1) addresses acquired intangibles, while column (2) addresses acquired intangibles, divided into definite and indefinite acquired intangibles. Column (3) shows the different associations for different intangible classes, divided into definite and indefinite lifetimes. Column (4) addresses whether acquired intangible assets are associated with receiving a goodwill CAM (*Goodwill CAM*). Acquired intangible variables (*Acquired_Int*, *Indef_Int*, *Indef_Marketing*, *Indef_Tech*, *Indef_Contract*, *Def_Int*, *Def_Tech*, *Def_NCA & Marketing*, *Def_Customer*, *Def_Contract*, *Other*) and *Goodwill* are scaled by total assets. All variables are defined in Appendix A. All models include controls, which are not reported for brevity, as well as industry (Fama-French 12) and year fixed effects. Standard errors are reported in parentheses below each coefficient estimate, with standard errors clustered by industry (Fama-French 12). *Economic* indicates the marginal effects at the mean (Greene (2019), Bushman et al. (2010)). The ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The period of observation is from 2019 until 2021 (totaling 3,578 observations).

Dependent Var.	*Intangible CAM*						*Goodwill CAM*	
	(1)		*(2)*		*(3)*		*(4)*	
	Coefficient	*Economic*	*Coefficient*	*Economic*	*Coefficient*	*Economic*	*Coefficient*	*Economic*
Acquired_Int	7.839***	0.371					1.233	0.130
	(0.647)						(0.975)	
Indef_Int			11.153***	0.522				
			(0.800)					
Indef_Marketing					15.545***	0.687		
					(2.129)			
Indef_Tech					27.344***	1.209		
					(4.827)			
Indef_Contract					16.125***	0.713		
					(3.133)			

(ctn. on next page)

Panel C: Acquired intangible assets and probability of receiving a critical audit matter (CAM) (ctn.)

Def_Int			4.861***	0.227				
			(0.968)					
Def_Tech					9.334***	0.413		
					(1.734)			
Def_NCA & Marketing					1.785	0.079		
					(8.677)			
Def_Customer					2.001	0.088		
					(1.724)			
Def_Contract					3.963	0.175		
					(6.029)			
Other					12.524	0.554		
					(8.248)			
Goodwill	-0.035	-0.002	0.185	0.009	-0.013	-0.007	4.197***	0.442
	(0.552)		(0.570)		(0.504)		(0.764)	
Goodwill CAM	1.407***	0.067	1.492***	0.070	1.565***	0.079		
	(0.150)		(0.154)		(0.259)			
Intangible CAM							1.347***	0.141
							(0.275)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,578		3,578		3,578		3,578	
Pseudo R^2	0.245		0.263		0.286		0.238	
Area under the ROC curve	0.845		0.857		0.867		0.829	

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IP Disclosure under IP Litigation

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ABSTRACT:

Legal disputes over the ownership of intellectual property (IP) have tripled over the last three decades costing hundreds of billion US-dollars to the US economy. In this paper, I examine how IP litigation affects the disclosure of subsequent innovation. Using the timeliness of patent pre-grant disclosures, I find that current IP litigation delays the disclosure of innovation (*delay effect*). This evidence is consistent with firms delaying the disclosure of similar technologies until IP uncertainty is resolved. In contrast, firms accelerate innovation disclosures when they have closed IP case experience (*deterrence effect*). While the delay effect leads to lower knowledge spillover, the deterrence effect mitigates incoming industry competition. I confirm these findings using the Supreme Court decision of *eBay vs. MercExchange* within a difference-in-differences design, which lowered the potential costs of enforcement for defendants of computer patents. Patents even become more informative when firms have closed IP litigation. Finally, weak IP institutions such as more lenient courts contribute to those disclosure effects. Overall, this paper highlights both negative and positive externalities of IP litigation on IP disclosures.

Key words: voluntary disclosure, litigation, innovation, patents, regulation.
JEL Codes: D23, G38, O30, O31, O33, O34, O38
Data availability: Data are available from the public sources cited in the text.

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Legal disputes over the ownership of intellectual property (IP) have tripled over the last three decades costing hundreds of billion US-dollars to the US economy. In this paper, I examine how IP litigation affects the disclosure of subsequent innovation. Using the timeliness of patent pre-grant disclosures, I find that current IP litigation delays the disclosure of innovation (*delay effect*). This evidence is consistent with firms delaying the disclosure of similar technologies until IP uncertainty is resolved. In contrast, firms accelerate innovation disclosures when they have closed IP case experience (*deterrence effect*). While the delay effect leads to lower knowledge spillover, the deterrence effect mitigates incoming industry competition. I confirm these findings using the Supreme Court decision of *eBay vs. MercExchange* within a difference-in-differences design, which lowered the potential costs of enforcement for defendants of computer patents. Patents even become more informative when firms have closed IP litigation. Finally, weak IP institutions such as more lenient courts contribute to those disclosure effects. Overall, this paper highlights both negative and positive externalities of IP litigation on IP disclosures.

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1. Introduction

"*Say I have lost all faith in patents, judges, and everything relating to patents.*"- Thomas Edison

The protection of intellectual property (IP) is at the core of the innovation process and a necessity for the comparative advantage of firms and an entire economy. However, rising numbers of IP litigation cases have become a burden to firms with an estimated cost of 300 billion to the US economy (Bessen et al. 2018). Thus, firms consistently innovate new technologies under the uncertainty of being sued for their existing technology. More importantly, many firms have to decide whether to disclose innovations, which could expose them to new litigation. In this paper, I examine how IP litigation affects the disclosure of subsequent innovation.

Understanding when and why firms disclose their innovations is important to policy makers and academic research (Tegernsee Experts Group 2012; Glaeser and Landsman 2021). Innovation is a major driver of economic growth because others can build on innovations due to knowledge spillovers (e.g., Solow 1957; Romer 1990). "However, others cannot build on an innovation and no spillovers occur until the innovation is disclosed" (Glaeser and Landsman 2021, page 292). IP litigation can alter IP disclosure and therefore, the spillover of knowledge, in two directions. On the one hand, firms can increase IP disclosures. IP lawsuits introduce uncertainty about the property rights of the defending firm's technology. Potential invalidations of IP can affect the economic rents of innovations and therefore the competitive position of the defending firm. To counteract those potential forces, firms can increase innovation disclosures to deter industry competition (Glaeser and Landsman 2021), and to better define their technological space to reduce the likelihood of future IP litigation. On the other hand, IP litigation can also lead to decreasing IP disclosure. Firms might not disclose valuable information about their innovations when the information could be favorable to strategic opponents, as for example to the opposing party or the jury (Wagenhofer 1990). Thus, it remains an empirical question whether and how IP litigation affects innovation disclosures.

In this paper, I examine the effect of IP litigation on the disclosure of subsequent innovation. First, I investigate whether and how IP litigation affects the disclosure of IP using the timing of patent pre-grant disclosures. For that, I develop different IP litigation measures to investigate differences among the timing and severity of IP litigation. Second, I exploit the Supreme Court decision of *eBay vs. MercExchange* in 2006 in a difference-in-differences design as a shock to IP litigation risk for further identification (Mezzanotti 2021). Third, I examine how lenient IP courts moderate those disclosure effects.

The timing of patent disclosures under the American Inventor Protection Act (AIPA) provides a rich setting to study my research questions. In November 2000, Congress passed the AIPA to reform patent disclosures and to reduce the costs of duplicate inventions and to foster knowledge spillovers and faster innovation (Kim and Valentine 2021; Lück et al. 2020). The AIPA mandates patent filers to disclose non-foreign protection filed pre-grant patents *no later than* 18 months after the filing of the patent with the United States Patent and Trademark Office (USPTO) regardless of being granted. Yet, firms can request the USPTO to publicly disclose their in-process patent application at any time during the 18-month period at the USPTO website, which provides them substantial discretion (Glaeser and Landsman 2021).

The timeliness of patent disclosures under the AIPA offers several advantages to study the effects of IP litigation over other measures of IP disclosures. First, the disclosure of a patent is a credible disclosure signal on the USPTO webpage. Other innovation measures, such as textual measures of 10-K reports (Merkley 2014; Bellstam et al. 2021) might be boilerplate disclosures of firm's technology. Patent disclosures, on the other side, must be concise and complete, so that others can replicate the disclosed innovation (35 USC § 112(a); Dyer et al. 2023). Moreover, innovators, competitors, and investors frequently use these disclosures for their decision-making (e.g., Ouellette 2012; Glaeser et al. 2020; Martens 2023). Second, the discretion of firms in the patent disclosure timing allows me to explore a closer link to the filing of IP lawsuits. Within the patent filing process, I am able to test my predictions in a sequential disclosure framework (Wagenhofer 1990; Somaya 2003). Put differently, I examine how firms *change* their IP disclosure behavior after the filing of an IP lawsuit. Third, I am able to measure the technological proximity of each filed patent to the patents that are litigated, which provides further identification.

To examine my research question, I combine several databases on IP litigation and patent application information with accounting- and market data. My analysis starts in 2003 and ends in 2013 covering 400,725 successful patent filings. To measure IP litigation, I construct different proxies from patent litigation cases based on its timing and its severity.[1] Patent litigation cases offer the advantage that I can connect litigated patents with filed patents through their technological proximity such as the same patent class. To examine different timing effects of IP litigation, I construct two variables for current and closed IP litigation. I measure current IP litigation when an IP lawsuit is filed between the filing and disclosure date of a patent. In contrast, I measure closed IP litigation when firms have closed an IP lawsuit 365 days before the patent filing. To measure the severity of IP litigation, I construct four proxies such as the number of IP lawsuits, number of litigated patents, an indicator variable for valuable patent litigated, and a negative capital market reaction to the IP lawsuit filing.

Results on the effect of current IP litigation on the disclosure of subsequent patents show that firms delay patent disclosures when a close technology is litigated (i.e. *delay effect*). I find that firms under ongoing IP litigation disclose patents with a delay of about 370 days, compared to the disclosure of similar class patents not involved in litigation. Moreover, patents under IP litigation are 29 percent more likely to be filed in the last 30 days before the disclosure deadline than a similar patent without IP litigation. This evidence is consistent with IP uncertainty

[1] While other forms of IP such as trademark or copyrights are also subject to litigation, patent lawsuits are the most common form of IP litigation in the US jurisdiction with over 97 percent of all filed IP lawsuits for public firms (Marco et al. 2017).

delaying IP disclosures. In contrast to current IP litigation, I find a negative association between closed IP litigation and IP disclosure (i.e. *deterrence effect*). Thus, firms accelerate patent disclosures when they have closed IP litigation in comparison to non-litigated patent disclosures. This evidence is consistent with the idea that firms accelerate IP disclosures when IP uncertainty is resolved and property rights have been strengthened. Taken together, while current IP litigation delays IP disclosures, closed IP litigation has positive effects on disclosure timing. I also investigate how the severity of IP litigation moderates these effects on patent disclosures. Across all four proxies, I find additional evidence that the *delay* effect is proportional to the severity of IP litigation risk.

Next, I investigate potential real effects of different disclosure strategies under IP litigation. In particular, I investigate how *delay* and *deterrence* effect affect two important dimensions of patent disclosures, the spillover of knowledge, measured by forward citations, and future industry competition. To benchmark different disclosure strategies under litigation, I separate patent disclosures into early and late patent disclosures based on the number of days from the filing to the actual disclosure. Regarding knowledge spillovers, I find that a late patent disclosure under current IP litigation is associated with less forward citations, while early disclosures under current IP litigation is not associated with citations. These results underline that the *delay effect* results in lower knowledge spillover, which can affect future innovation. Regarding industry competition, I find no effects of current IP litigation on future industry competition. However, I find that an early IP disclosure under closed IP litigation is significantly less negative associated with future industry competition than a late disclosure under closed IP litigation. This evidence implies that an early patent disclosure can mitigate potential negative effects of closed IP litigation on future competition in deterring incoming market participants.

To provide further evidence on the specific mechanisms of these effects and to alleviate potential endogeneity concerns (e.g., Schantl and Wagenhofer 2023) I exploit the Supreme

Court decision of *eBay vs. MercExchange* in 2006 in a difference-in-differences design. The court decision increased the requirements for plaintiffs to file an automatic injunction for patents in the computer & communication space leaving requirements for patents from other technology classes unchanged. After the court decision, automatic injunctions have become less likely to be filed for those patents. Thus, the ruling in *eBay vs. MercExchange* reduced IP litigation risks for defendants of computer & communication patents (Bereskin et al. 2023; Mezzanotti 2021). More importantly, this unexpected court ruling might be plausibly exogenous with regard to patent disclosures, outside of its effect on IP litigation risk. Consistent with my prior findings, I find that computer-related patents have a significantly lower disclosure delay in the post period, i.e. firms accelerate disclosures timing after the court ruling. This evidence is consistent with my prior results that lower IP litigation risk likelihood, in form of a lower injunction likelihood, correlates with accelerated disclosures of pre-grant patents.

I corroborate my main findings with three additional analyses. First, I investigate whether weak IP institutions contribute to the IP disclosure effects using the court of the Eastern District of Texas (EDT) as a setting of weak IP enforcement. The EDT has been criticized for plaintiff friendly enforcement (Connors 2019). Regarding IP litigation, I find evidence that a high exposure to plaintiff-friendly IP enforcement regimes significantly delay the disclosure of patents, i.e. plaintiff-friendly courts contribute to those disclosure effects. Second, I investigate how the information content of patents changes when firms experience both current and closed IP litigation. Using the patent disclosure quality data of Dyer et al. (2023), I find evidence for more disclosure information in the form of more pictures and words, when a firm has settled IP litigation. Yet, I find no evidence that current IP litigation affects patent information content. This evidence is consistent with accelerated and better patent disclosures after IP litigation. Third, I investigate the robustness of my results in two alternative settings: around the Leahy Smith Invents Act in 2011 and with another proxy of litigation risk from the literature (Francis et al. 1994; Kim and Skinner 2012). In total, insignificant results indicate that the distinct effect of IP litigation on IP disclosure is neither explained by changes in patent disclosure requirements nor the litigious environment of a firm.

My study's contribution is threefold. First, I extend the literature on the relationship between disclosure and litigation, where the predominant focus has been on shareholder litigation. While several papers find mixed findings in this setting (e.g., Kim and Skinner 2012; Bourveau et al. 2018; Schantl and Wagenhofer 2023), less is known about the effects of litigation on disclosures outside the shareholder litigation setting. While class action lawsuits capture misbehavior of management, IP litigation targets specific assets and therefore the potential comparative advantage of a firm (Galasso and Schankerman 2018). My paper contributes to this stream of literature by providing first evidence of how different IP litigation risks affect the IP disclosure behavior of firms.

Second, I contribute to the literature on IP enforcement, which is also of interest for legal academics and practitioners (see e.g., Bessen and Meurer 2013; Bessen et al. 2018; Mezzanotti 2021; Bereskin et al. 2023). While many studies focus on the effects of IP litigation on investment, innovation, and competition, less is known about potential effects on information environments. Glaeser et al. (2023) find evidence that lawsuit parties collect private information to prepare of IP lawsuits. Kim et al. (2023) find evidence that judicial inefficiencies in IP enforcement can reduce innovative output. I contribute to this literature by providing the first evidence that IP litigation can have both positive and negative effects on the disclosure of innovation. More importantly, plaintiff-friendly IP courts contribute to those effects.

Third, I contribute to the literature on IP disclosures (see Glaeser and Lang (2023) for a review). Ahci et al. (2023) find evidence that IP disclosures provide feedback effects to filing firms affecting corporate decision-making. My paper is closely related to Glaeser and Landsman (2021). They find evidence that firms time their patent disclosures to deter product market competition. In contrast, I find a countervailing effect to patent disclosures, which is current IP litigation. Moreover, I contribute to this literature by identifying IP litigation as a crucial factor in the IP disclosure process.

The paper is structured as follows: Section 2 describes the institutional background and the development of my hypothesis. Section 3 describes research design, data sources and measures of IP disclosure and litigation, while section 4 describes my main results. Section 5 provides additional analyses, while section 6 concludes.

2. Institutional background and hypothesis development

2.1 Patent litigation in the US

Innovation is a central driver of economic growth because others can build on innovations due to knowledge spillovers (e.g. Solow 1957; Romer 1990). In order to protect innovations, firms can file for intellectual protection through patents, trademarks, or copyrights. Then, potential infringements of innovation can be enforced and prosecuted. While many IP lawsuits are filed within the US jurisdiction, over 97 percent of all cases for public firms are about patent litigation (Marco et al. 2017).

The purpose of a patent is to grant a temporary monopoly over an innovation in exchange for detailed disclosure. Thus, a patent holder can extract economic rents for the innovation as a reward for his successful investment in technology. Yet, the patent system has been critiqued recently as the enforcement of patent rights has become a large burden for both regulators and firms. The number of IP lawsuits has tripled over the last thirty years (Bessen et al. 2018). Large firms such as Apple and Google have faced over 50 IP lawsuits per year. Even smaller firms such as startups are constantly targeted by IP litigation (Lanjouw and Schankerman 2004; Appel et al. 2019). Given the strong rise in IP litigation, several scholars question whether the costs of the patenting process and enforcement have exceeded the benefits. Some even call for the abolishment of the patent system (Jaffe and Lerner 2011; Cohen et al. 2019).

In the case of legal disputes, courts are the institutions to enforce property rights. For intellectual property (IP), the court should decide on the legal claims of a patent. However, the costs of IP litigation have risen over the last thirty years due to several reasons. On the hand, technology boundaries of patents have become unclear and unpredictable (Bessen and Meurer 2008). Additionally, courts have been favorable in granting large monetary awards to parties, even for patents that are of small technological contribution (Government Accountability Office 2013; Chen et al. 2023). This has led to new business ventures such as patent assertion entities.[2]

The rise in IP litigation increased the costs of innovation on several dimensions. On the macroeconomic level, Bessen et al. (2018) estimate the costs of IP litigation of over $300 billion to the US economy. Moreover, IP litigation affects cumulative innovation and productivity growth (Ryu 2022). On the firm level, the total fees per lawsuit can amount to $1-$25 million (American Intellectual Property Law Association 2013). According to a survey by RPX Corp. (2015), the mean of combined legal and settlement costs per NPE litigation is $5.6 million, even if the defendant firm wins the case. Moreover, IP lawsuits also affect the profitability of firms. When a patent is infringed, the technology cannot be used, which ultimately affects the comparative advantage of the firm.

2.2 Hypothesis development

Given the discussion above, IP litigation has become a burden for firms to consider in their overall innovation strategy. The rise of IP litigation affected the investment behavior of firms and their peers. In general, the risk of inadvertent infringement of intellectual property can reduce the economic rents of inventing (Galasso et al. 2013; Galasso and Schankerman 2015). For instance, Lemley and Feldman (2016), Cohen et al. (2019), and Mezzanotti (2021) find

[2] Patent assertion entities are also commonly referred to as patent trolls. Usually, their business model can be described by the acquisition and monetization of patents. In particular, they do not produce or sell any products covered by the patented technology. Instead, they earn revenues through licensing agreements with patents acquired from others and legal disputes with other firms. Proponents of patent assertion entities argue that they create a market for innovation buying and selling patents. Opponents argue that they are among the reasons for rising IP litigation numbers (Cohen et al. 2019). For more information on patent assertion entities, see Cotropia et al. (2014).

evidence that excess IP litigation can reduce investments in innovation at defendant firms. In particular, firms shift their innovation strategy to foster investments of more exploitative, rather than explorative innovation (Lee et al. 2021). Additionally, firms ramp up investments in defensive tools, such as a large legal department, which seems to have some effects on deterring attacks (Cohen et al. 2019). They also hire executives with legal expertise, which should reduce the threat of future litigation (Dai et al. 2023). These investments are likely reducing the economic rents for innovating. From a macro perspective, litigation also reduces the knowledge spillover among innovators (Ryu 2022), which is crucial for fostering future innovation. While IP litigation seems to have effects on competition and the investment behavior of firms, less is known about the effects of IP litigation on information environments of firms. In particular, it is unclear how IP litigation may affect the disclosure of subsequent innovation.

Understanding when and why firms disclose innovation is important to policy makers and academic research (e.g. Tegernsee Experts Group 2012; Glaeser and Landsman 2021). Innovation is a central driver of economic growth because others can build on innovations due to knowledge spillovers (e.g. Solow 1957; Romer 1990). “However, knowledge spillovers cannot occur until the innovation is disclosed“(Glaeser and Landsman 2021 page 292). The disclosure of innovation can also prevent costly duplication of research efforts and can affect the allocation of capital because of information asymmetry around innovations (Aboody and Lev 2000; Lück et al. 2020).

IP litigation can alter the disclosure decision of subsequent innovation and therefore, the spillover of knowledge, in two directions. On the one hand, IP litigation can increase IP disclosure. In general, the filing of an IP lawsuit introduces uncertainty about the property rights of the defending firm’s technology. Unlike physical assets, IP assets can be readily copied which makes them difficult to enforce (Crouzet et al. 2022). IP lawsuits can help in redefining those property rights, again. Moreover, IP litigation presents a shock to the competitive position of a firm (Lanjouw and Schankerman 2001; Galasso and Schankerman 2018). Potential invalidations of IP rights can affect the economic rents of innovations and therefore the competitive position of the defending firm. For instance, Research in Motion (RIM), producer of the Blackberry cell phone, lost its competitive position in the cell phone market due to a long and costly IP litigation case against the patent assertion entity NTP (Mezzanotti 2021; Bereskin et al. 2023). In the end, RIM paid $ 612.5 million in settlement fees, which was about half of RIMs annual revenues at that time. To counteract those potential forces, firms can increase their innovation disclosures to deter new industry competition (Hughes and Pae 2015; Glaeser and Landsman 2021). Moreover, firms can also make their IP disclosures better to delineate their technological space, which can prevent future IP litigation.

On the other hand, IP litigation can also lead to decreasing IP disclosure. Wagenhofer (1990) underlines that firms might not disclose valuable information at first, when the information could be favorable to strategic opponents, as for example to the opposing party or the jury in a lawsuit. In the case of shareholder litigation, managers may withhold bad information to prevent a lawsuit (Bourveau et al. 2018; Schantl and Wagenhofer 2023). In the case of IP litigation, firms can withhold IP disclosures due to the uncertainty of the litigated technology. Several technological advances might build on prior technologies that could be part of an ongoing IP lawsuit. Hou et al. (2023) find evidence that many patents are connected with each other due to strategic patenting. Thus, firms might withhold information about new technologies until IP uncertainty is resolved.

IP litigation might also not affect innovation disclosures for two reasons. First, several IP lawsuits might not be material to the defending firm. They could rest on untenable claims, or the opposing party is relatively small, thus, the likelihood of wining is high for defendants. Consistent with this argument, Bessen (1995) finds evidence that capital markets do not react to all IP lawsuits, only to the material ones. Second, the technology, that is litigated, does not have many technological similarities with the technology that the firm is intending to disclose.

Particularly large tech firms operate in several market segments with different and non-overlapping technologies.

In sum, it remains an empirical question whether and how IP litigation affects the disclosure of innovation. I test the following hypothesis in alternative form:

Hypothesis: IP litigation affects the disclosure of innovation.

3. Research design and descriptive statistics

3.1 Measures of IP disclosure

I measure IP disclosure using pre-grant patent level disclosures in the post American Inventor's Protection Act (AIPA) regime. The timing of patent disclosures under the AIPA provides a rich setting to study my research question. The setting mandates patent filers to disclose domestic pre-grant patents *no later than* 18 months after the filing of the patent with the United States Patent and Trademark Office (USPTO) regardless of being granted. Yet, firms can request the USPTO to publicly disclose their in-process patent application at any time during the 18-month period at the USPTO website (Glaeser and Landsman 2021).

The timeliness of patent disclosures under the AIPA offers several advantages to study the effects of IP litigation over other measures of IP disclosure. First, the disclosure of a patent is a credible disclosure signal on the USPTO webpage. Other innovation measures, such as textual measures of 10-K reports (Merkley 2014; Bellstam et al. 2021) might be boilerplate disclosures of firm's technological progress. Patent disclosures must be concise and complete, so that others can replicate the disclosed innovation (35 USC § 112(a); Dyer et al. 2023). Moreover, innovators, competitors, and investors frequently use these disclosures for their decision-making (e.g. Ouellette 2012; Glaeser et al. 2020; Martens 2023). Second, text-based disclosures are sticky measures of innovation, i.e., they do not possess a lot of meaningful time variation. This makes them hard to use for empirical tests that need time series variation such as difference tests in firm's IP litigation risk. Third, the discretion of firms in the patent disclosure timing allows me to explore a closer link to the filing of IP lawsuits. Within the patent filing process, I am able to test predictions in a sequential disclosure framework (Wagenhofer 1990; Somaya 2003). Put differently, I examine how firms *change* their IP disclosure behavior after the filing of an IP lawsuit. Fourth, I am able to measure the technological proximity of each filed patent to the patents that are litigated, which provides further identification. Appendix B provides an example of a patent disclosure from a patent from Biogen Inc.

I follow Glaeser and Landsman (2021) and construct three patent disclosure measures based on the timing of pre-grant disclosures. The first measure is the logarithm of the days between the filing a patent and the actual disclosure on the USPTO website, less 14 weeks for the processing of the patent application (Glaeser and Landsman 2021).[3] The second measure is the percentage disclosure delay measuring the ratio between days of actual disclosure divided by maximum number of days. The third measure is an indicator variable, whether the actual disclosure has been conducted 30 days before the disclosure deadline. It allows me to investigate whether firms choose to disclose right before the deadline.

3.2 Measures of IP litigation

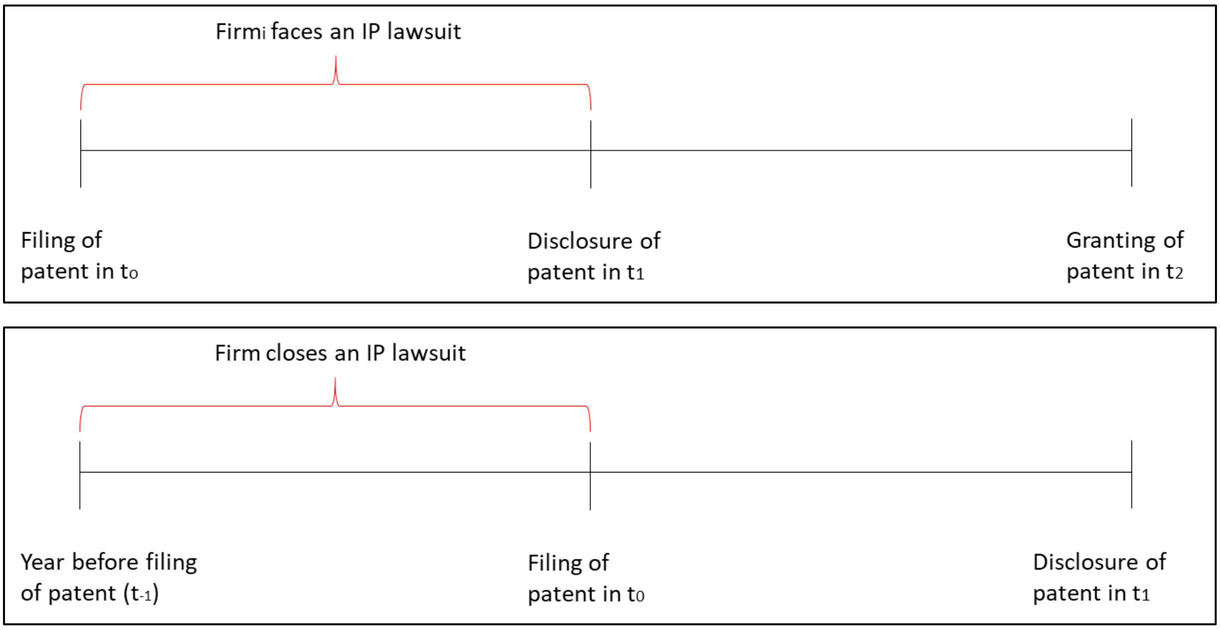
To investigate the effect of IP litigation on IP disclosure, I construct two measures for IP litigation risk: current and closed IP litigation. Current IP litigation (*IP_litigation*) aims to capture the effect of an IP lawsuit that the firm is facing before their disclosure decision. Firms might change their IP disclosure strategy when they are litigated. I define a patent to be filed under IP litigation, i.e. *IP_litigation* equal to one, when the firm faces one or more IP lawsuits between the filing and the disclosure date of patent. The advantage of this identification is that it mimics sequential disclosure models (e.g. Wagenhofer 1990; Somaya 2003) and allows me to investigate how firms *change* their IP disclosure strategy under IP litigation.

[3] The USPTO takes about 14 weeks to process a patent application. Thus, I exclude those 14 weeks from my timing measures (Glaeser and Landsman 2021). Yet, inferences remain unaffected if I neglect this 14-week window.

Second, I measure closed IP litigation through closed IP lawsuits. Closed IP litigation (*Closed_IP_litigation*) aims to measure the resolving of IP uncertainty within the last year before patent filing. I define *Closed_IP_litigation* equal to one, if the firm has closed an IP lawsuit one year before the filing date of the patent, zero otherwise. Thus, while current IP litigation captures new IP uncertainty, closed IP litigation captures resolved IP uncertainty. Figure 1 summarizes my identification strategy within the patent disclosure process after the enactment of the AIPA with both current and closed IP litigation.

Figure 1: Sequence of the patent process and definition of IP litigation variables

This figure presents the patent protection process after the American Inventor Protection Act (AIPA) in November 2000. I define current IP litigation equal to one, if the firm faces an IP lawsuit in the period between the filing and the disclosure of the patent. I define closed IP litigation when the firm closes an IP lawsuit in the period between one year before filing and the filing of the patent.



Further, I investigate how the severity of IP litigation risk affects IP disclosure behavior. Firms with more IP litigation risk might differ in their IP disclosure strategy than lower risk firms. Given that there is no perfect measure for IP litigation severity, I measure the severity of IP litigation using four empirical constructs: number of IP lawsuits, number of litigated patents, an indicator variable for a valuable patent litigated, and an indicator variable for an IP lawsuit with a severe negative capital market reaction. For my first measure, *Ln(1+IP Lawsuit Number)*, I follow Kiebzak et al. (2016) and take the natural logarithm of all IP lawsuits filed in the period between filing and disclosure day. While the number of IP lawsuits captures the amount of IP litigation, it does not say anything about the amount and value of the intellectual property in dispute. For instance, while some lawsuits are about one patent, other lawsuits are about entire patent portfolios. Therefore, I construct my second measure, *Ln(1+litigated patents)*, as the natural logarithm of the number of litigated patents. Complementary to this measure, my third measure, *Valuable_Patent_litigated*, captures the actual patent value at risk.

Valuable patents can represent the most valuable technology of a firm and therefore its comparative advantage. I measure valuable patents litigated using the Kogan et al. (2017) patent value database. I denote an IP lawsuit as valuable to the firm, i.e. *Valuable_Patent_litigated* equal to one, if the litigated patent has a value above the median of all litigated patents, zero otherwise. Lastly, I construct my fourth measure based on the capital market reaction of the defendant. I follow Chen et al. (2023) and use negative cumulative abnormal returns (CAR) in a [-1, +1] three-day window around the IP lawsuit announcement using a market model.[4] *Negative_IP_Reaction* is one if the firm has a negative CAR of two percent around the lawsuit filing, zero otherwise.[5] Appendix A provides more details of all my variables of interest.

3.3 Baseline specification

To investigate my research question, I follow Glaeser and Landsman (2021) and estimate a baseline disclosure model on patent application level. This model compares the timing of subsequent patent pre-grant disclosures under IP litigation with patents not facing IP litigation risk. Thus, I estimate the following specification on patent level:

$$IP\ Disclosure_{i,j,t} = \beta_0 + \beta_1 IP\ Litigation_{t-1} + Controls_{i,t-d} + Patent\ Class\ x\ Year\ FE$$
$$+ Industry\ FE + \varepsilon_{i,j,t} \qquad (1)$$

where i indexes patent applicants (i.e., i indexes individual firms); j indexes patent applications; and t indexes application years. *IP Disclosure* captures my different measures of IP disclosure, while IP litigation captures different proxies for IP litigation risks. All firm variables are

[4] Other studies including Bhagat et al. (1998) and Lerner (1995) have also investigated CARs around IP litigation announcements. To underline the severity, I calculate the economic significance of a material IP lawsuit in terms of dollar values. Around the announcement of a material IP lawsuit, the average firm occurs a loss in market value of around $18.6 million.

[5] This capital market measure of IP litigation is not without flaws. Bessen and Meurer (2012) note that this measure might be subject to substantial measurement error. Some IP lawsuits “are not publicly disclosed by the firm (or noted in the media), and that there is sometimes a delay between the court filing date and the announcement date by the firm/media” (Bereskin et al. 2023 page 3).

measured as of the most recent fiscal year prior to the patent application filing (the t-d). I cluster standard errors on industry level.[6]

I also include a vector of several time varying industry-, firm-, and patent specific controls. First, I include different measures for the competitive environment of a firm. Since industry competition is multidimensional and therefore hard to capture in one specific measure, I employ three established measures within the competition literature: First, I measure industry concentration using the Herfindahl Hirschman Index (*HHI*) on industry level using sales.[7] Second, I include the product market fluidity measure (*Fluidity*) of Hoberg et al. (2014) to measure potential product competition threats of the firm. Third, I control for technological competition using the number of citations (Glaeser and Landsman 2021).

Second, firm specific controls include variables such as the size of firm (*Size*) using the natural logarithm of total assets[8], leverage (*Lev*), which is the book value of total debt divided by total assets, market-to-book ratio (*Market-to-Book*), and R&D expenditures (*R&D*). I scale R&D expenditures by total assets. I replace missing values of R&D expenditures with zeroes. Additionally, I employ an indicator variable for missing R&D (*Missing_R&D*) which equals one if data on R&D expenditures are missing; zero otherwise (Koh and Reeb 2015). I also control for the capital dependency of firms (Rajan and Zingales 1998). I measure external capital dependence (*External_Capital_Reliance*) as capital expenditures plus R&D expenditures minus the cash flow of operating activities, divided by capital expenditures plus R&D expenditures (Rajan and Zingales 1998; Plumlee et al. 2015; Glaeser and Landsman 2021). I also include variables for the firm's financial performance such as return on assets

[6] One might argue that clustering of standard errors within this empirical design can be also appropriate on firm- and even on patent class level (Petersen 2009; Cohen et al. 2019; Mezzanotti 2021). I cluster standard errors on industry level, as many IP lawsuits are concentrated among certain industries such as the computer and the business services industry (see Table 1, Panel A). However, a different clustering of standard errors does not change statistical inferences of any of my results.
[7] I also test the robustness of my results by defining the HHI index by total assets instead of total sales. Results remain qualitatively the same.
[8] Results remain unchanged if I include other commonly used firm size proxies such as the natural logarithm of sales and the natural logarithm of the market value of equity (Dang et al. 2018).

(*ROA*) and loss-making years (*Loss*). *ROA* is measured by income before extraordinary items scaled by total assets, while *Loss* is an indicator variable equal to one if the net income is negative, zero otherwise. I also include a cash-to-assets ratio (*Cash*) as cash-rich firms tend be targeted by aggressive plaintiffs such as patent assertion entities (Cohen et al. 2019).

Third, I include patent specific controls such as the patent value (*Patent_Value*) measured on granting date (Kogan et al. 2017) and the technological breadth of the patent (*Breadth*) using the Bowen et al. (2023) database. Additionally, I include *ln (Days to Latest Possible Disclosure)* as a control when I use days until disclosure as the dependent variable. All control variables are defined in Appendix A. To mitigate the effect of outliers, I winsorize all independent variables, that are not measured in its logarithm, at the 1^{st} and 99^{th} percent levels.

I additionally add interacted US patent class and filing year fixed effects (*Patent Class x Year FE*) and Fama-French 48 industry fixed effects (*Industry FE*). While industry fixed effects control for unobserved differences between industries, *Patent Class x Year FE* control for unobserved regulatory differences between patent classes within each year. Thus, this fixed effect structure allows me compare patents with and without IP litigation risks filed in the same patent class in the same year.

3.4 Identification strategy

A potential concern is that IP disclosure is endogenous with respect to the disclosing firm. Schantl and Wagenhofer (2023) find theoretical evidence in the shareholder litigation setting that disclosures might also spur follow-on litigation (see also Kim and Skinner 2012; Bourveau et al. 2018). This might also be the case for IP disclosures as new patent disclosures could spur new patent lawsuits. Another potential concern is that I can only observe actual IP litigation risk in form of filed IP lawsuits. However, plaintiffs such as patent assertion entities send out demand letters before the actual filing of a lawsuit. Defendants, then, can react to these demand letters in form of negotiating royalty agreements with the plaintiffs to prevent a lawsuit filing, which is unobservable. Taken together, the relation between IP litigation and IP disclosure might be endogenous among many dimensions.

To address these limitations, I study the effect of IP litigation on IP disclosure using potentially exogenous variation to IP litigation risk, the *eBay vs. MercExchange* Supreme Court decision on May 30, 2006 (Bereskin et al. 2023; Mezzanotti 2021). This unexpected lawsuit outcome affected the litigation risk of defendants through the strengthening of injunction requirements. In particular, the Supreme Court decision changed the success rate for plaintiffs to file an automatic injunction. “Injunction is a remedy that can be requested by a plaintiff. If granted by a court, an injunction forces the defendant to stop using any technology covered by the contested patents, irrespective of the magnitude of the infringement” (Mezzanotti 2021, page 7365). Before 2006, a plaintiff that was able to prove a violation had essentially the automatic right to obtain a permanent injunction. “In other words, the norm was that a permanent injunction should be issued when infringement was proven” (Mezzanotti 2021, page 7365). Exceptions to this rule were quite uncommon and mostly due to reasons of public interest. The availability of a quasi-automatic injunction grants a lot of power to plaintiffs in IP negotiations (Hall and Ziedonis 2001; Mezzanotti 2021). Thus, the Supreme Court ruling strengthened the role of defendants.

I estimate the effect of the Supreme Court ruling in a difference- in-differences design on patent unit level:

$$IP\ Disclosure_{i,j,t} = \beta_0 + \beta_1 ICT\_Patent\ \ x\ Post_{t-1} + Controls_{i,t-d} + Fixed\ Effects + \varepsilon_{i,j,t} \quad (2)$$

My treatment variable is *ICT_patent*, which is equal to one if a patent falls in the NBER patent category "Computers & Communications", zero otherwise. *Post* equals one if a patent is filed after May 30, 2006, zero otherwise. I also include all control variables as defined in the previous section. Further, I include different fixed effect structures, such as industry, time, patent class, and firm fixed effects for further identification. I cluster standard errors on industry level.

3.5 Data

For my investigation, I employ and match data from different sources. I begin by retrieving the patent database from Kogan et al. (2017), which has key data on the filing dates of utility patents.[9] Kogan et al. (2017) contain all utility patents granted to public firms from 1926 to 2016.[10] Next, I merge the patent database with the filing database of the USPTO to retrieve the disclosure dates of each patent. I follow Hall et al. (2001) and Hall et al. (2005) and remove the last three years (2014-2016) to alleviate potential concerns about truncation bias.

Next, I identify firms and patents under IP litigation. For this, I employ the patent litigation docket reports dataset published by the United States Patent and Trademark Office (USPTO).[11] This dataset combines IP lawsuits from different IP law databases such as Pacer, Lex Machina, and Lexis Nexis to provide a comprehensive dataset on IP lawsuits.[12] I only keep IP lawsuits,

[9] I thank the authors for providing the data on their webpage.
[10] I do not investigate design patents because their disclosure requirements differ from utility patents. In particular, design patents are disclosed on the granting day, thus they are excluded from the enhanced disclosure requirements of the AIPA (Chan et al. 2022).
[11] The data is publicly available under the following link: https://www.uspto.gov/ip-policy/economic-research/research-datasets/patent-litigation-docket-reports-data.
[12] The patent litigation docket reports database of the USPTO even goes back until 2000. Yet, I start my investigation in 2003, because this database does not allow for the identification of litigated patents before 2003. For more information on this database, see Marco et al. (2017).

in which patents are the object of dispute and firms clearly marked as defendants.[13] Keeping only the lawsuits, where patent filers are defendants, allows me keep the unobserved effects between different lawsuit parties fixed. Plaintiff and defendants have different motives in IP lawsuits and different positions in the market, which affects the likelihood of winning. I merge patent litigation data and annual accounting data using a fuzzy name-matching algorithm based on the firm name.[14] Finally, I use accounting- and financial market data from Compustat and CRSP.

For my final dataset, I require non-missing data on all my dependent and independent variables. Further, I exclude patents of firms that are in the financial and utility industry and firms with a market value of equity of less than 5 million dollars (i.e. penny stocks). I also drop industries, which filed less than 50 patents.[15] I also remove singleton observations, i.e., observations that are nested within my fixed effect structure (Correia 2015). My final dataset consists of 400,725 patents from 1,667 firms filed between January 1, 2003, and December 31, 2013.

Following Glaeser and Landsman (2021), I only focus on successfully applied patents. For unsuccessful applications, it is hard to measure the effect of IP litigation on IP disclosure given that they may never disclose the pre-grant patent. Focusing on successfully applied patents also allows me to isolate the effect of IP litigation on the applicants' disclosure decision from other important factors like the underlying economics of successfully patenting (Farre-Mensa et al. 2020).

I also investigate my research question for public firms only to ensure all necessary data for all my tests. Therefore, my results might not be generalizable to private firms such as startups, which are commonly targeted by IP litigation (Lanjouw and Schankerman 2004; Appel

[13] This dataset also contains IP lawsuits, in which trademarks and copyrights are objects of disputes. Sometimes even, the object of dispute is unknown. I delete those IP lawsuits from my investigation.
[14] I manually check the accuracy of my matches to ensure proper matching between those datasets.
[15] Results remain qualitatively the same if I include those industries in my sample.

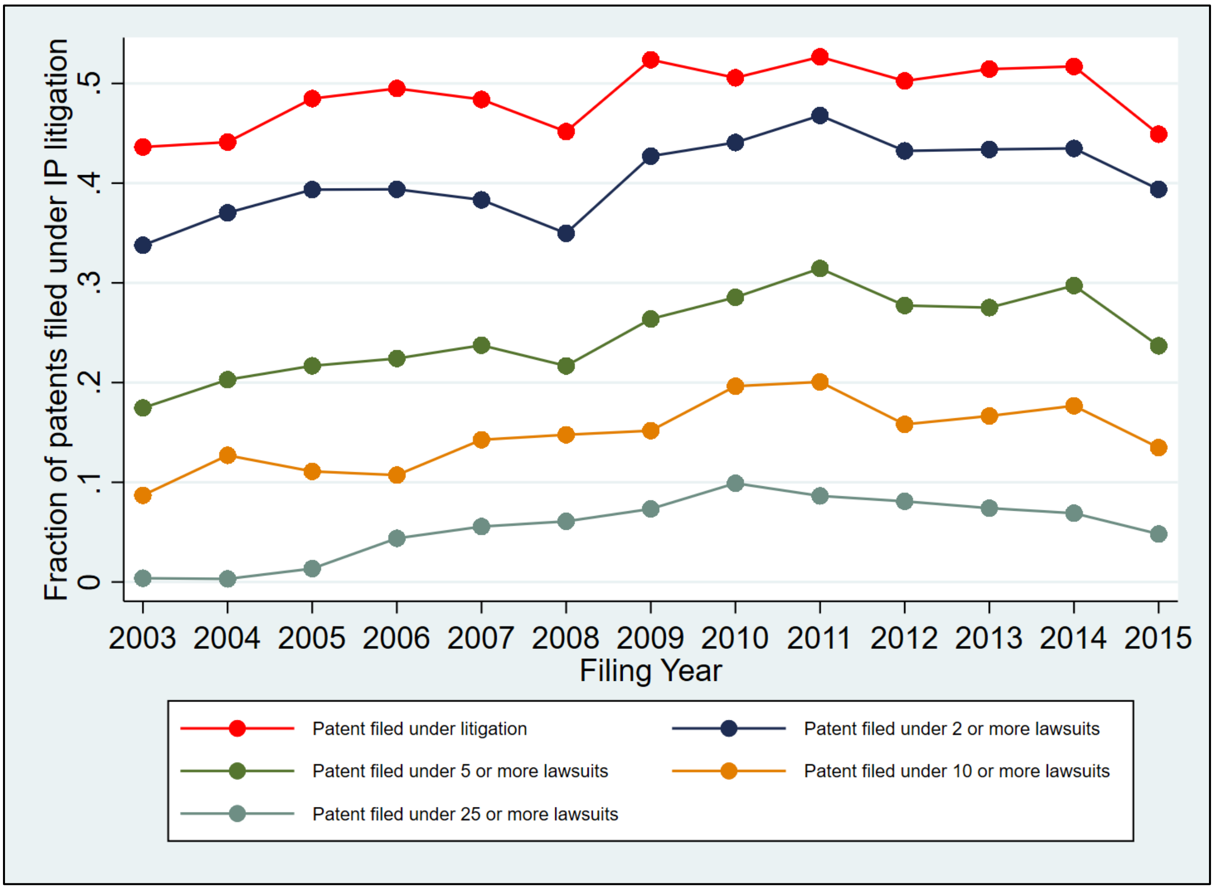
et al. 2019). Yet, the large majority of innovation is carried out by large and publicly traded firms (Kogan et al. 2017). IP litigation is also apparent for many of those firms.

3.6 Descriptive statistics

Previous literature suggests that IP litigation is a common phenomenon for innovating firms. Figure 2 plots the frequency of filed patents under IP litigation. The plot suggests that about 40 percent of all patents are filed under litigation. Numerous patents are even filed under severe IP litigation with the number of lawsuits being higher than 25 cases. Thus, IP litigation is a significant component in the IP disclosure decisions of firms.

Figure 2: Occurrence of patent filings under IP litigation

This figure presents the filing of patents under current IP litigation. The different lines highlight how many lawsuits have been filed when the firm disclosed the patent. The period of observation is from 2003 until 2013.



Summary statistics reveal the same patterns. Table 1 reports descriptive statistics for my sample. Panel A reports the industry distribution of new patents filed under current and closed IP litigation. Quite strikingly, new patents are consistently filed under current IP litigation across many industries. Most patents, which are filed under current IP litigation, are located in the electronic equipment, computer, and the business services industries, which is consistent with prior evidence (Mezzanotti 2021). Those industries also have the largest severity of IP litigation, in which many patents are filed under ten or more IP lawsuits. Regarding closed IP litigation, I observe the same patterns as for current IP litigation. Taken together, high IP litigation occurrences seems to be clustered among a few industries such as business services and electronic equipment. Yet, IP litigation appears in almost every industry, not in just a few sectors.

Table 1: Industry distribution of IP litigation and descriptive statistics

This table reports summary statistics for the industry distribution of IP lawsuits and the dependent and independent variables used in this study. Panel A reports industry distributions of the filing of patents and the likelihood of filing patents under current and closed IP litigation. I define industries by using the Fama-French 48 industry classifications (excluding the financial and utility industry). Panel B reports descriptive statistics on IP disclosure and IP litigation measures. Panel C reports descriptive statistics on all control variables used. The definitions of the variables can be found in Appendix A. The period of observation is from 2003 to 2013 (totaling 400,725 observations).

Panel A: Industry composition of patents filed under current and closed IP litigation

Industry Composition	*Patents filed*	*Patents disclosed under current IP litigation*	*Patents disclosed under 10 or more IP lawsuits*	*Patents disclosed after closed IP litigation*
Agriculture	1,349	1,275	0	1,349
Food Products	375	24	0	111
Candy &Soda	102	1	0	33
Beer & Liquor	622	24	0	33
Tobacco & Products	548	0	0	0
Recreation	1,155	245	7	625
Entertainment	1,812	60	0	63
Printing & Publishing	64	23	0	23
Consumer Goods	3,874	1,371	6	2,098
Apparel	2,309	45	0	50
Healthcare	175	41	0	60
Medical Equipment	18,753	4,638	9	6,048
Pharmaceutical Products	14,715	6,395	39	7,715
Chemicals	12,426	118	0	566
Rubber & Plastic Product	106	15	0	21
Textiles	50	1	0	2
Construction Materials	1,933	850	1	1,304
Steel Works etc.	266	38	0	26
Machinery	16,635	4,551	2	6,184
Electrical Equipment	2,691	307	7	505
Automobiles & Trucks	15,812	10,644	638	9,587
Aircraft	11,051	2,400	10	2,342
Shipbuilding	136	0	0	6
Defense	1,262	387	5	359
Industrial Metal Mining	56	0	0	0
Petroleum & Gas	15,753	3,959	2	4,382
Communication	16,034	12,561	7,869	11,070
Business Services	100,121	33,245	13,151	33,484
Computers	45,504	14,579	3,933	12,980
Electronic Equipment	98,634	64,192	10,070	68,997
Measuring Equipment	7,580	2,299	2	3,146
Business Supplies	6,624	5,032	5	5,312
Shipping Containers	212	2	0	23
Transportation	255	89	0	91
Wholesale	191	29	0	44
Retail	1,540	1,177	805	1,201
Total	**400,725**	**170,617**	**25,403**	**179,840**

Panel B: Descriptive statistics on IP disclosure and IP litigation variables

Variables	*Mean*	*SD*	*Median*	*p75*	*p90*	*p99*
IP disclosure measures						
Ln (Days to Disclosure)	5.330	1.173	6.107	6.120	6.125	6.888
Percentage Disclosure Delay	0.713	0.330	1	1	1	1
Disclosure 30 Days before Deadline	0.525	0.499	1	1	1	1
Ln (File Size)	13.843	0.565	13.794	14.144	14.528	15.534
Ln (Number Figures)	2.142	0.789	2.197	2.565	3.045	3.989
Ln (Number of words)	8.386	0.691	8.393	8.811	9.228	10.161
Ln (FOG Index)	2.977	0.124	2.979	3.056	3.127	3.273
Ln (Specificity)	1.735	0.949	1.662	2.360	3.054	4.002
IP litigation measures						
IP_litigation	0.426	0.494	0	1	1	1
Closed_IP_litigation	0.449	0.497	0	1	1	1
Same_Tech Litigated	0.096	0.294	0	0	0	1
Same_Tech_Closed	0.125	0.331	0	0	1	1
Different_Tech_Litigated	0.353	0.478	0	1	1	1
Different_Tech_Closed	0.301	0.459	0	1	1	1
Ln(1+IP Lawsuit Number)	0.639	0.912	0	1.099	1.946	3.638
Ln(1+litigated patents)	0.860	1.229	0	1.609	2.773	4.554
Valuable_Patent_litigated	0.039	0.194	0	0	0	1
Negative_IP_Reaction	0.044	0.204	0	0	0	1
EDT_Exposure	0.255	0.436	0	1	1	1
EDT_Non_Exposure	0.171	0.376	0	0	1	1

Panel C: Descriptive statistics on control variables

Variables	*Mean*	*SD*	*Median*	*p75*	*p90*	*p99*
HHI	-1.828	0.784	-1.830	-1.451	-0.656	-0.030
Fluidity	6.809	2.660	6.532	8.024	10.076	15.698
Loss	0.119	0.324	0.000	0.000	1.000	1.000
ROA	0.069	0.103	0.081	0.126	0.169	0.241
R&D	0.068	0.057	0.051	0.091	0.121	0.324
Missing R&D	0.033	0.180	0.000	0.000	0.000	1.000
Leverage	0.180	0.143	0.177	0.269	0.339	0.631
External Capital Reliance	-0.661	0.426	-0.742	-0.574	-0.294	1.484
Cash	0.329	0.217	0.272	0.467	0.633	0.959
Size	9.954	1.803	10.328	11.434	11.699	12.537
Market-to-Book	3.991	2.763	3.439	5.260	7.548	14.585
Number Cites	1.174	1.141	1.099	1.792	2.773	4.500
Patent_Value	1.759	1.169	1.757	2.516	3.271	4.662
Breadth	0.288	0.249	0.260	0.520	0.634	0.735
ln(Possible Disclosure)	6.359	0.181	6.306	6.315	6.339	7.104

Panel B reports my IP disclosure and my IP litigation measures. Consistent with Glaeser and Landsman (2021), the disclosure timing of pre-grant patents is clustered among the beginning and the end of the 18 months period. In general, the mean patent disclosure delay is about 325 days and the median is about 445 days. Regarding IP litigation, I observe a large heterogeneity among my measures. Table 1, Panel C, reports summary statistics for my control variables. All control variables are in line with prior research on IP disclosure in the patent setting (Glaeser and Landsman 2021; Kim and Valentine 2023).

4. Main results

4.1 IP disclosure under current and closed IP litigation

First, I investigate how current and closed IP litigation affect the disclosure timing of subsequent patents. I measure IP disclosure under current IP litigation if firms face an IP lawsuit in the time between filing and disclosure date of a patent. In contrast, closed IP litigation is measured when firms have settled an IP lawsuit 365 days before the filing of the patent.

Table 2 reports the results for the effect of current and closed IP litigation on patent disclosure delays. In particular, these tests compare patent applications filed with IP litigation against patent applications without IP litigation in the same patent class in the same year. Thus, this allows me to hold patent characteristics as well as filing regulation fixed.

Table 2: Patent disclosure delay under IP litigation

This table presents OLS regressions of patent disclosure delays as a function of closed and current IP litigation. Panel A reports results for the effect of current and closed IP litigation. Panel B disaggregates current and closed IP litigation into same and different technologies litigated. Same Technology is measured when filed and litigated patents are from the same US patent class. Panel C reports differences in coefficients between same and different technologies. All other variables are defined in Appendix A. All models include controls, as well as industry (Fama-French 48) and interacted patent class with filing year fixed effects (Patent Class*Year FE). Standard errors are reported in round parentheses below each coefficient estimate, with standard errors clustered by industry. The ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The period of observation is from 2003 to 2013 (totaling 400,725 observations).

Panel A: IP litigation on IP disclosure

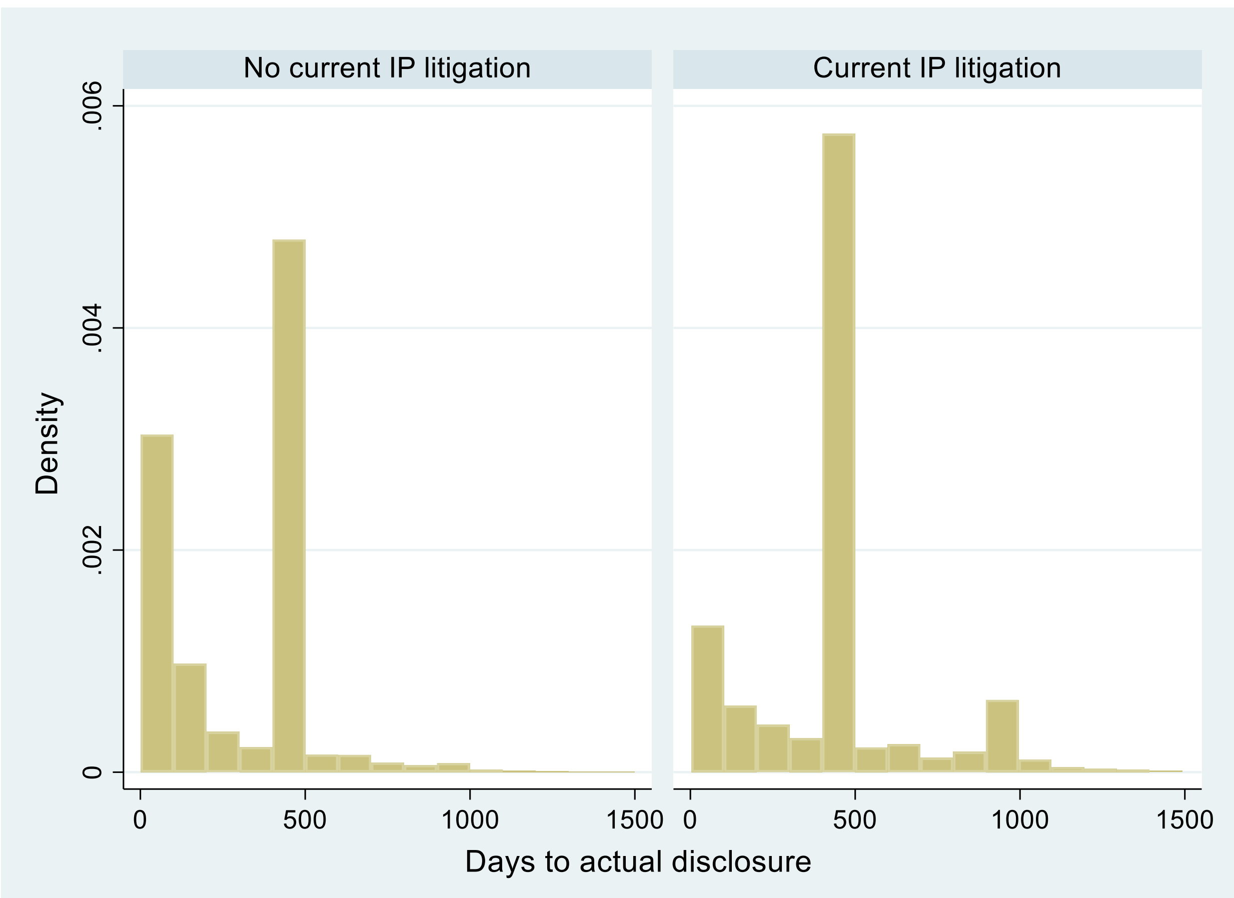
Dependent Var.	*Ln (Days to Disclosure)*	*Ln (Days to Disclosure)*	*Percentage Disclosure Delay*	*Percentage Disclosure Delay*	*Disclosure 30 Days before Deadline*	*Disclosure 30 Days before Deadline*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
IP_litigation	0.765***	0.512***	0.233***	0.168***	0.286***	0.220***
	(0.085)	(0.056)	(0.021)	(0.015)	(0.027)	(0.026)
Closed_IP_litigation	-0.408***	-0.601***	-0.122***	-0.172***	-0.150***	-0.202***
	(0.072)	(0.119)	(0.018)	(0.031)	(0.023)	(0.041)
IP_litigation ×Closed_IP_litigation		0.464***		0.120***		0.122***
		(0.119)		(0.032)		(0.044)
HHI	0.088**	0.091***	0.031***	0.032***	0.047***	0.048***
	(0.034)	(0.029)	(0.010)	(0.009)	(0.013)	(0.012)
Fluidity	0.005	0.004	0.001	0.001	0.001	0.001
	(0.007)	(0.006)	(0.002)	(0.002)	(0.003)	(0.003)
Loss	-0.108***	-0.108***	-0.036***	-0.036***	-0.042*	-0.042*
	(0.030)	(0.030)	(0.013)	(0.012)	(0.023)	(0.023)
ROA	0.467**	0.428**	0.157**	0.148**	0.243*	0.233*
	(0.192)	(0.182)	(0.068)	(0.065)	(0.123)	(0.120)
R&D	1.057***	0.991***	0.370***	0.353***	0.609***	0.592***
	(0.250)	(0.235)	(0.092)	(0.087)	(0.163)	(0.158)
Missing R&D	0.465**	0.452**	0.116**	0.113*	0.141*	0.137*
	(0.188)	(0.190)	(0.056)	(0.056)	(0.071)	(0.072)
Leverage	0.471**	0.485**	0.166***	0.169**	0.281***	0.285***
	(0.180)	(0.196)	(0.059)	(0.062)	(0.092)	(0.096)
External Capital Reliance	-0.048**	-0.038*	-0.014**	-0.011**	-0.012	-0.009
	(0.021)	(0.019)	(0.006)	(0.005)	(0.010)	(0.009)
Cash	-0.178**	-0.177**	-0.044*	-0.044*	-0.048	-0.047
	(0.066)	(0.067)	(0.023)	(0.023)	(0.036)	(0.036)
Size	0.031**	0.026**	0.015***	0.014***	0.030***	0.029***
	(0.012)	(0.012)	(0.004)	(0.004)	(0.007)	(0.006)
Market-to-Book	0.000	-0.000	-0.001	-0.001	-0.003	-0.003
	(0.003)	(0.003)	(0.001)	(0.001)	(0.003)	(0.003)

Number Cites	0.008	0.008	-0.002	-0.002	-0.004	-0.005
	(0.009)	(0.009)	(0.003)	(0.003)	(0.003)	(0.003)
Patent_Value	-0.020	-0.021	-0.008	-0.008	-0.015	-0.015
	(0.016)	(0.015)	(0.005)	(0.005)	(0.009)	(0.009)
Breadth	0.027	0.026	0.008	0.008	0.007	0.006
	(0.061)	(0.063)	(0.020)	(0.020)	(0.033)	(0.034)
ln(Possible Disclosure)	1.788***	1.796***				
	(0.138)	(0.132)				
Patent Class*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	400,725	400,725	400,725	400,725	400,725	400,725
Adjusted-R^2	0.224	0.228	0.173	0.177	0.173	0.174

Column (1) estimates the effects of current and closed IP litigation on the logarithm of the days of patent disclosures delays. Regarding current IP litigation, I find a significantly positive association to patent disclosures delays (i.e. *delay effect*). A coefficient of 0.765 suggests that being litigated is associated with a 114 percent increase in the time until patent disclosure.[1] In economic terms, IP litigation leads to an increase in patent disclosure delays of about 370 days around the mean. Thus, firms delay the disclosure of innovation because of IP uncertainty. Figure 3 displays the significant shift in patent disclosure respectively.

Figure 3: *Delay effect* of current IP litigation on patent disclosure delays

This figure presents histograms of the density of days to actual disclosure of a patent under current IP litigation. The left histogram presents patents disclosed without current IP litigation. The right histogram plots patents disclosed with current IP litigation. The period of observation is from 2003 until 2013.

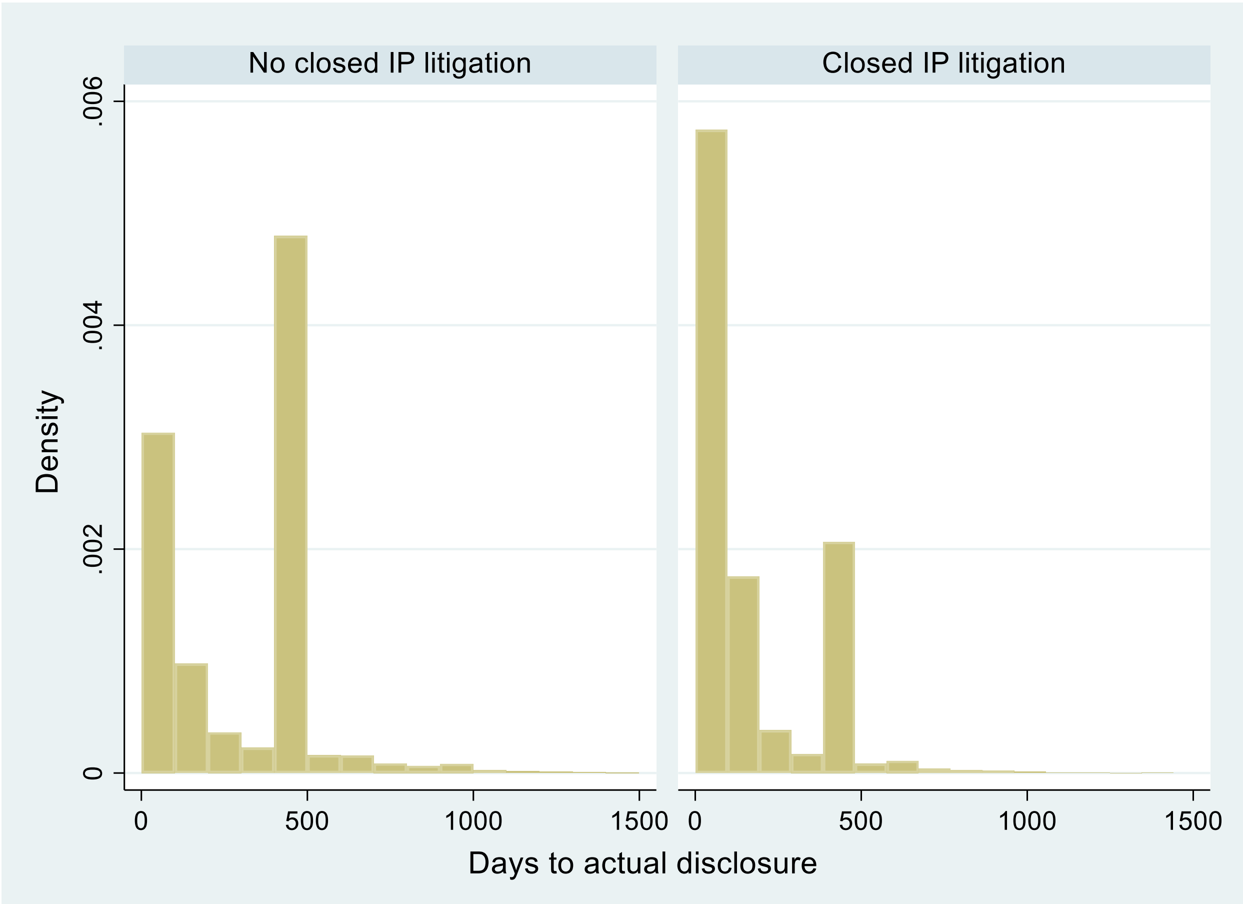


[1] The increase in patent disclosure is calculated the following: $(e^{0.765}-1)*100$.

In contrast to current IP litigation, I find a negative and significant coefficient for *Closed_IP_litigation*, significant on the one percent level. A coefficient of -0.408 suggests that resolved IP uncertainty leads to an acceleration of patent disclosures of about 50 percent in comparison to patents without closed IP litigation (i.e. *deterrence effect*). Figure 4 shows graphically that firms accelerate patent pre-grant disclosures after the closing of IP lawsuits. Additionally, all control variables are in line with Glaeser and Landsman (2021). In particular, I find the same significantly opposing effect of increased competition (*HHI*). Thus, while increased industry competition accelerates patent disclosures, current IP litigation counteracts this effect by delaying patent disclosures. Next, I estimate the interaction effect of both *IP_litigation* and *Closed_IP_litigation* to investigate whether the delay- or deterrence effect dominates the patent disclosure decision. Column (2) presents a significant and positive effect on the interaction term (0.464).

Figure 4: *Deterrence effect* of closed IP litigation on patent disclosure delays

This figure presents histograms of the density of days to actual disclosure of a patent under closed IP litigation. The left histogram presents patents disclosed without closed IP litigation. The right histogram plots patents disclosed with closed IP litigation. The period of observation is from 2003 until 2013.



In Column (3), I investigate the effect of current and closed IP litigation on the percentage of patent disclosure delays. Consistent with Column (1), *IP litigation* is positively associated with the percentage in patent disclosure delays. Put differently, patent disclosures are significantly delayed when the firm is under current IP litigation. In contrast, *Closed_IP_litigation* is negatively associated with the percentage of disclosure delays, suggesting an acceleration of patent disclosures. Additionally, the interaction term of current and closed IP litigation is again positive underlining that the *delay effect* is stronger, as reported in Column (4).

In Column (5), I examine whether patents are disclosed at the end of the disclosure deadline. Here, I estimate a linear probability model to determine the likelihood of disclosing patents before the deadline when litigated.[2] Consistent with my prior results, I find a positive and significant association between *IP_litigation* and *Disclosure 30 Days before Deadline*. In economic terms, if patent applications face IP uncertainty, firms are about 29 percent more likely to disclose the patent in the month before its deadline.

Taken together, while current IP litigation delays the disclosure of pre-grant patents, the resolution and experience of closed IP litigation fosters earlier patent disclosure. Thus, IP litigation does not always have negative externalities, but it can also have positive externalities in form of faster IP disclosures when IP uncertainty has been resolved.[3]

To provide a better understanding about the mechanism of those different effects, I split my IP litigation variables into same (*Same_Tech_litigated*; *Same_Tech_closed*) and different technologies litigated (*Different_Tech_litigated*; *Different_Tech_closed*). Firms might choose to disclosure patents differently when the litigated technology is close to the filed one. Thus, this disaggregation allows me to investigate the technological proximity of litigated and filed patents. I define patents of close technological proximity, i.e., *Same_Tech_litigated* equal to one, if the filed patent and the litigated patent belong to the same US patent class.

[2] To test the robustness of this result, I also estimate a logit model with and without fixed effects (Greene 2019). Results remain unchanged with regard to my inferences.

[3] I do the following steps to investigate the robustness of these results: First, I estimate this specification without and within the pharmaceutical industry. Prior evidence suggests that pharmaceutical firms disclose their innovations early onwards in form of clinical trial disclosures (e.g. Cao et al. 2018; Capkun et al. 2023). Second, I estimate each specification with firm- instead of industry fixed effects. Firm fixed effects alleviate potential concerns regarding unobserved differences between firms. Moreover, it shows how firms change IP disclosure behavior when they are litigated vs. not litigated (i.e. within firm estimator). Third, I estimate this specification without and within the three major patent filing industries "Electronic equipment", "Computer", and "Business services". Results remain unchanged regarding all these robustness tests. Results are reported in Appendix C of the paper.

Panel B: Same technology litigated and IP disclosure

Dependent Var.	*Ln (Days to Disclosure)*	*Percentage Disclosure Delay*	*Disclosure 30 Days before Deadline*
	(1)	*(2)*	*(3)*
Same_Tech_Litigated	1.093***	0.330***	0.409***
	(0.088)	(0.023)	(0.032)
Same_Tech_Closed	-0.624***	-0.184***	-0.231***
	(0.071)	(0.018)	(0.025)
Different_Tech_Litigated	0.679***	0.207***	0.252***
	(0.091)	(0.023)	(0.031)
Different_Tech_Closed	-0.406***	-0.122***	-0.152***
	(0.067)	(0.017)	(0.021)
Controls	Yes	Yes	Yes
Patent Class*Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	400,725	400,725	400,725
Adjusted-R^2	0.239	0.190	0.186

Panel C: Differences between same and different technologies

Differences of coeff.			
	(1)	*(2)*	*(3)*
Same_Tech_Litigated vs. Different_Tech_Litigated	0.414***	0.123***	0.157***
Same_Tech_Closed vs. Different_Tech_Closed	-0.624***	-0.062***	-0.079***

Table 2, Panel B, reports results for the different effects of IP litigation on patent disclosures conditional on the technological proximity of litigated and filed patent. Again, I find the opposing effects of current and closed IP litigation, significant for both same and different technologies across all four columns. More importantly, the effect for *Same_Tech_litigated* (1.093), in Column (1), is significantly larger than for *Different_Tech_litigated* (0.679). Table 2, Panel C, reports differences in coefficients and their significance. This evidence is consistent with the argument that the filing of new technologies is significantly delayed when a related technology is currently litigated. Moreover, this effect remains the same across the other IP disclosure proxies as well. For closed IP litigation, *Same_Tech_closed* is also significantly different from *Different_Tech_closed*.

In particular, patent disclosures are more accelerated when IP lawsuits with related technology are settled.

Additionally, I investigate the disclosure effects for different firm- and patent characteristics. Previous literature finds evidence that the existence of IP litigation depends on specific firm- and patent characteristics (e.g. Lanjouw and Schankerman 2004; Cohen et al. 2019). For firm characteristics, I examine how a different lifecycle stage of a firm (Lanjouw and Schankerman 2004; Dickinson 2011; Vorst and Yohn 2018; Appel et al. 2019) affects the disclosure decision. Results indicate that growth firms delay the disclosure of their pre-grant patents even further than mature firms do. These results are consistent as those firms usually have the highest legal costs and cannot defend their market position. Regarding patent characteristics, I examine cross-sectional differences between origination and continuation patents (Hou et al. 2023; Righi 2023). Patent applications are further delayed when a patent is continuation patent, i.e., they rely on a prior patent. Results are reported in Appendix D1 and D2 of the paper.

4.2 Severity of IP litigation

Next, I investigate if the IP disclosure delay effect differs if current IP litigation severs. Several patents are not only filed and disclosed under one IP lawsuit, but many firms face several IP lawsuits at the same time. For instance, Google Inc. had 56 IP lawsuits in 2015, in which they regularly filed new patents. Moreover, the severity and costs of IP lawsuits might differ pending on the opposing party. While some firms are targeted by other firms or patent assertion entities (Cohen et al. 2019) regularly, others might be initiated by private persons or smaller firms having lower bargaining power (Lanjouw and Schankerman 2004). Thus, the effect of IP litigation on IP disclosure might not be proportional.

The severity of litigation risk is a multidimensional construct, as one measure might not reflect the entirety of IP litigation risk. Therefore, I measure the severity of IP litigation risk using four empirical constructs: the logarithm of the number of current IP lawsuits, the number of patents litigated, an indicator variable for a valuable patent litigated, and a material IP lawsuit with a severe negative capital market reaction. Detailed definitions of the variables can be found in Appendix A.

Table 3 reports the results for the effects of different proxies for the severity of IP litigation on IP disclosures. I report regression results for *Ln (Days to Disclosure)* only for brevity.[4] In column (1)-(4), I estimate the isolated effect of each severity proxy on the timing of patent disclosures. I find positive and significant associations between all four proxies and patent disclosure delays. Consistent with my prior evidence, I find that current IP litigation delays patent disclosures and it is proportional within the number of IP lawsuits.

[4] I have also investigated the effect of IP litigation severity on my other three patent disclosure proxies. Results remain qualitatively the same.

Table 3: Severity of IP litigation

This table presents OLS regressions of patent disclosure delays as a function of the severity of current IP litigation. Column 1 reports coefficients for the number of IP lawsuits. Column 2 reports coefficients for the number of litigated patents. Column 3 reports coefficients for lawsuits if valuable patents are litigated. Column 4 reports coefficients if the firm faces a lawsuit, which led to a negative capital market reaction. Column 5 reports coefficients for all proxies together in one specification. All other variables are defined in Appendix A. All models include controls, which are not reported for brevity, as well as industry (Fama-French 48) and interacted patent class with filing year fixed effects (Patent Class*Year FE). Standard errors are reported in round parentheses below each coefficient estimate, with standard errors clustered by industry. The ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The period of observation is from 2003 to 2013 (totaling 400,725 observations).

Dependent Var.	*Ln (Days to Disclosure)*				
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
Ln(1+IP lawsuit number)	0.403***				0.399***
	(0.043)				(0.086)
Ln(1+litigated patents)		0.284***			-0.003
		(0.026)			(0.055)
Valuable_Patent_litigated			0.645***		0.113*
			(0.068)		(0.059)
Negative_IP_Reaction				0.188***	-0.055
				(0.030)	(0.041)
Controls	Yes	Yes	Yes	Yes	Yes
Patent Class*Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	400,725	400,725	400,725	400,725	400,725
Adjusted-R^2	0.234	0.229	0.192	0.184	0.234

Lastly, I repeat the analysis with all proxies within one specification. Column (5) reports the results. Results indicate that the number of IP lawsuits and valuable patents litigated capture the severity of IP litigation. Number of patents litigated and negative capital market reaction remain insignificant. In sum, the results of my different proxies underpin that the severity of IP litigation can even worsen the delay in patent disclosures, i.e., the effect of IP litigation on IP disclosure is proportional.

4.3 Consequences of early / late IP disclosures under IP litigation

Next, I investigate potential real consequences of both delay and deterrence effect under IP litigation. In particular, I investigate how different disclosure strategies under IP litigation affect knowledge spillover and industry competition. First, I investigate potential effects on knowledge spillovers measured by the number of citations using linear regressions.[5] I separate patent disclosure delays into early and late patent disclosures. This allows me to investigate how a late or early patent disclosure strategy maps into knowledge spillovers and industry competition. Table 4 reports results.

Table 4: Consequences of early/late patent disclosure under IP litigation

This table presents OLS regressions of consequences of an early and late disclosure under IP litigation. Column 1 reports coefficients for the effect of current and closed IP litigation on the number of forward citations. Column 2 reports coefficients for an early and late disclosure strategy under current and closed IP litigation on the number of forward citations. Column 3 for the effect of current and closed IP litigation on future industry competition. Column 4 reports coefficients for an early and late disclosure strategy under current and closed IP litigation on future industry competition. All other variables are defined in Appendix A. All models include controls, which are not reported for brevity, as well as industry (Fama-French 48) and interacted patent class with filing year fixed effects (Patent Class*Year FE). Standard errors are reported in round parentheses below each coefficient estimate, with standard errors clustered by industry. The ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The period of observation is from 2003 to 2013 (totaling 400,725 observations).

Dependent Var.	*Number Cites*	*Number Cites*	*HHI*	*HHI*
	(1)	*(2)*	*(3)*	*(4)*
IP_litigation	0.008		-0.059*	
	(0.026)		(0.029)	
Closed_IP_litigation	0.028		-0.174***	
	(0.022)		(0.049)	
Late_Disc_IP_litigation		-0.119***		0.085
		(0.027)		(0.067)
Early_Disc_IP_litigation		0.003		0.015
		(0.026)		(0.038)
Late_Disc_closed_IP_litigation		0.018		-0.207**
		(0.045)		(0.081)
Early_Disc_closed_IP_litigation		-0.045		-0.101***
		(0.032)		(0.022)
Controls	Yes	Yes	Yes	Yes
Patent Class*Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	400,725	400,725	400,725	400,725
Adjusted-R^2	0.253	0.254	0.684	0.676

[5] Several papers argue that count variables, as a dependent variable, can be problematic in linear regression models (Cohn et al. 2022). Thus, I also estimate the effects of IP litigation on citations using a fixed-effect Poisson model. Inferences do not change with regard to the results.

In Column (1), I find no evidence between both current and closed IP litigation and technological spillovers. In Column (2), however, I find that a late patent disclosure under IP litigation is negatively associated with the number of citations. For an early patent disclosure, I find insignificant results. Regarding industry competition, Column (3) confirms evidence that closed IP litigation is associated with a lower market position (e.g. Lanjouw and Schankerman, 2001). More importantly, Column (4) separates IP litigation proxies into early and late IP disclosures. I find evidence that an early IP disclosure is less associated with a loss in market position than a late patent disclosure under closed IP litigation.

4.4 *eBay vs. MercExchange* Supreme Court decision

A potential concern of my prior results is that IP disclosure could also affect the likelihood of being litigated. Schantl and Wagenhofer (2023) find theoretical evidence in the shareholder litigation setting that disclosures might also spur follow-on litigation (see also Kim and Skinner 2012; Bourveau et al. 2018). Another potential concern is that I can only observe actual IP litigation risk in form of filed IP lawsuits. However, plaintiffs such as patent assertion entities send out demand letters before the actual filing of a lawsuit, which may never lead to actual IP litigation. Taken together, the relation between IP litigation and IP disclosure might be endogenous among many dimensions.

To address these limitations, I study the effect of IP litigation risk on IP disclosures in a difference- in-differences design. In particular, I explore the *eBay vs. MercExchange* Supreme Court decision on May 30, 2006, as a shock to IP litigation risk (Bereskin et al. 2023; Mezzanotti 2021). This unexpected lawsuit outcome affected the litigation risk of defendants through the strengthening of injunction requirements.

I restrict my sample to patent applications two years before and after the treatment (2004-2008). Additionally, I follow Bereskin et al. (2023) and exclude patents from the drugs & medical sector to form a proper control group.[6] Column (1) estimates the effect of the reduction of an injunction likelihood on patent disclosure using industry- and semiannual fixed effects only. Column (2) adds covariates, while Column (3) adds patent class fixed effects. Column (4) estimates the specification with firm and instead of industry fixed effects, thus, it investigates within firm change in IP disclosure behavior. I predict that reduced IP litigation risk for computer patents should accelerate disclosure timing for those patents, while not affecting other patent categories.

Table 5: Patent disclosure delay after the *eBay vs. MercExchange* ruling

This table presents OLS regressions of patent disclosure delays around *the eBay vs. MercExchange* Supreme Court ruling in a difference-in-differences design. *ICT_patent* is equal to one, if the patent is NBER patent category" computers & communications", zero otherwise. *Post* is equal to one for patents filed after the July 1, 2006, zero otherwise. Column 1 estimates the effect with time (semi-annual) and industry (Fama-French-48) fixed effects. Column (2) adds control variables, while Column (3) adds patent class fixed effects. Column (4) estimates the effects with firm, patent class, and time fixed effects. All other variables are defined in Appendix A. Standard errors are reported in round parentheses below each coefficient estimate, with standard errors clustered by industry. The ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The period of observation is from 2004 to 2008 (totaling 219,667 patent observations).

[6] The literature identifies potential difficulties in identifying pharmaceutical and biotechnology patents as an appropriately defined control group for this setting (Mezzanotti and Simcoe 2019; Bereskin et al. 2022). One reason is that the Supreme Court ruling in Mayo vs. Prometheus (2012) held that certain innovations were not patent eligible (specifically, if the innovation is based on "laws of nature"); although the Supreme Court rulings occurred outside the restricted sample period, the lawsuit was filed in 2004 and the district court held the patents invalid in 2008. Moreover, the National Research Council (2006) highlights some of the unique changes in life science patents around this time period, relating to the development of proteomics and the human genome project, including NIH policies relating to availability of data and encouragement of use of certain patented technology, and court rulings such as In re Fisher (2005), where the court ruled the patents relating to "expressed sequence tags" are not patentable (without "specific and substantial utility"). Another important legal ruling in this period is Merck KGaA vs. Integra LifeSciences I (2005), where the Supreme Court protected certain defendants from litigation when the work was related to an FDA submission (Mezzanotti 2021).

Dependent Var.	*Ln (Days to Disclosure)*			
	(1)	*(2)*	*(3)*	*(4)*
ICT_Patent ×Post	-0.094***	-0.053***	-0.046***	-0.040**
	(0.018)	(0.015)	(0.016)	(0.018)
ICT_Patent	0.111***	0.004		
	(0.039)	(0.030)		
HHI		0.055	0.052	0.280
		(0.050)	(0.049)	(0.189)
Fluidity		0.006	0.006	-0.007
		(0.010)	(0.010)	(0.009)
Loss		-0.034	-0.035	0.051
		(0.059)	(0.059)	(0.050)
ROA		0.779***	0.768***	0.506***
		(0.219)	(0.219)	(0.155)
R&D		1.154***	1.124***	-0.220
		(0.322)	(0.322)	(1.023)
Missing R&D		0.256***	0.254**	0.199***
		(0.094)	(0.095)	(0.045)
Leverage		0.368*	0.365*	-0.407**
		(0.188)	(0.188)	(0.175)
External Capital Reliance		-0.083***	-0.084***	0.016
		(0.029)	(0.028)	(0.015)
Cash		0.008	0.002	-0.269**
		(0.037)	(0.037)	(0.125)
Size		0.062***	0.062***	0.026
		(0.012)	(0.012)	(0.048)
Market-to-Book		0.004	0.004	0.002
		(0.004)	(0.004)	(0.011)
Number Cites		0.016**	0.015**	0.025***
		(0.007)	(0.007)	(0.008)
Patent_Value		0.003	0.003	-0.090***
		(0.023)	(0.023)	(0.016)
Breadth		-0.302**	-0.177*	-0.175***
		(0.119)	(0.094)	(0.054)
ln(Possible Disclosure)		1.698***	1.697***	1.687***
		(0.118)	(0.119)	(0.123)
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	No
Patent Class FE	No	No	Yes	Yes
Firm FE	No	No	No	Yes
Observations	219,667	219,667	219,667	219,667
Adjusted-R^2	0.038	0.139	0.140	0.202

Table 5 reports results for this prediction. First, I find a positive and significant coefficient on *ICT_patent* suggesting that computer patents are significantly disclosed at later days. More importantly, results show both negative and statistically significant coefficients on the interaction term of *ICT_patent* and *Post*. In Column (1), a coefficient of -0.098 suggests that the reduction of the injunction likelihood for computer & communication patents lead to an offset of this patent disclosure delay. In Column (2), adding control variables reduces the effect of the Supreme Court decision to about 5 percent, yet still significant on the one percent level. Moreover, column (3) suggests that disclosures within this patent class (i.e. within patent class estimator) are accelerated after the Supreme Court decision. Consistent with my prior evidence, I find that a reduction of IP litigation risk leads to lower patent disclosure delays. Taken together, lower injunction likelihoods for software patents reduce the threat of potential IP litigation costs for defending firms, which accelerates pre-grant disclosures of patents of the computer & communication sector.

5. Additional analyses

In the following section, I supplement my main analyses with additional results regarding the effects of IP litigation on the information content of patents (i.e., disclosure quality of patents, see Dyer et al. 2023), the effect of weak enforcement regimes, and additional robustness tests.

5.1 IP enforcement regimes and IP disclosure

First, I investigate how weak IP enforcement institutions contribute to the delay of IP disclosures under IP litigation. A strong institutional enforcement regime is mandatory for the effectiveness of patent protection and follow-on innovation (Lerner 2002; Kim et al. 2023). Yet, judicial inefficiencies have spurred large criticism among legal scholars about the effectiveness of current US patent protection and the wellbeing of the entire patent system (Moore 2001).

Here, I examine whether a plaintiff friendly interpretation of the patent law has effects on the disclosure timing of pre-grant patents. Plaintiff- or defendant friendly courts may have real effects on the reporting of innovation as it has in other litigation settings (Franke et al. 2024). For this, I exploit the district court of Eastern Texas as a setting of plaintiff friendly IP litigation. Legal scholars argue that this court is favorable towards plaintiffs (Moore 2001; Jacobsmeyer 2018). In fact, several scholars denote these actions as "court shopping".[7] To investigate the effect of the plaintiff-friendly IP enforcement, I separate current IP litigation into two variables, *EDT_Exposure* and *EDT_Non_Exposure*, based on the exposure of the firm to this court in the filing of this patent.

Table 6: Patent disclosure delay under weak IP enforcement regimes

This table presents OLS regressions of patent disclosure delays as a function of a weak enforcement regime. *EDT_Exposure* is an indicator variable equal to one, when firm has a high exposure to IP litigation in the Eastern district of Texas, zero otherwise. *EDT_Non_Exposure* is an indicator variable, when the firm does not have a high exposure to IP litigation in the Eastern district of Texas, zero otherwise. All other variables are defined in Appendix A. All models include controls which are not reported for brevity, as well as industry (Fama-French 48) and interacted patent class with filing year fixed effects (Patent Class*Year FE). Standard errors are reported in round parentheses below each coefficient estimate, with standard errors clustered by industry. The ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The period of observation is from 2003 to 2013 (totaling 400,725 patent observations).

Dependent Var.	*Ln (Days to Disclosure)*	*Percentage Disclosure Delay*	*Disclosure 30 Days before Deadline*
	(1)	*(2)*	*(3)*
EDT_Exposure	0.681***	0.208***	0.262***
	(0.089)	(0.028)	(0.037)
EDT_Non_Exposure	0.359***	0.112***	0.125***
	(0.092)	(0.028)	(0.037)
Controls	Yes	Yes	Yes
Patent Class*Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	400,725	400,725	400,725
Adjusted-R^2	0.217	0.165	0.168

[7] The US legislation recognized this problem of "court shopping" (Moore 2001; Connors 2019) and introduced new regulation at the end of 2016 to counteract this phenomenon. In particular, in *TC Heartland LLC v. Kraft Foods*, the Supreme Court tightened regulation to narrow venues to the state of incorporation of the defendant only, invalidating the clause "where the defendant has committed acts of infringement and has a regular and established place of business". The phenomenon of court shopping also appears in non-US jurisdictions (Jacobsmeyer 2018).

Table 6 reports the results for this effect. Both effects of *EDT_Exposure* and *EDT_Non_Exposure* are significantly positively associated with patent disclosure delays. This result is consistent across all three columns. More importantly, *EDT_Exposure* is significantly larger than *EDT_Non_Exposure*. Economically speaking, a large exposure to plaintiff-friendly IP courts is associated with 45 percent increase in patent disclosure delays compared to a low exposure.[8] Consistent with Franke et al. (2024), plaintiff-friendly courts in IP rulings increase disclosure delays of subsequent innovations. Particularly, they increase the IP litigation costs of firms leading to substantial IP reporting delays. Taken together, patents are later disclosed when firms have a large exposure to weak IP enforcement institutions, which is consistent with a high likelihood of IP litigation costs.

5.2 Patent quality characteristics

My prior tests show that firms delay their subsequent patent disclosures under IP litigation, while accelerating when they have recently settled an IP lawsuit. Yet, IP disclosure is a multidimensional construct (Cao et al. 2018). That implies that IP litigation might not only affect the timing of patent disclosures, but other dimensions of IP disclosures as well. One dimension could also be the disclosure quality of patents. 35 USC § 112(a) states that patent disclosures should be “full, clear, concise, and exact” enough to permit a person familiar with the technology to recreate the patented innovation (Dyer et al. 2023). Yet, patents differ significantly in their disclosure quality they provide (Dyer et al. 2023). This discrepancy in the disclosure quality of patents might also be affected by ongoing and closed IP litigation. On the one side, IP litigation could make patent disclosures more informative as litigated firms decide to define their intellectual property rights more clearly. On the other side, disclosure quality of patents can deteriorate.

[8] The increase in patent disclosure is calculated the following: $(e^{(0.681-0.359)}-1)*100$.

I follow Dyer et al. (2023) and measure patent disclosure quality using five measures: file size, number of figures, number of words, the Gunning-FOG Index for patent readability, and the specificity of patents.[9] More details on the construction of the used variables can be found in Appendix A as well as in Dyer et al. (2023). I estimate the effect of IP litigation on patent disclosure quality using OLS regressions within the same regression framework than in my previous tests.

[9] I thank the authors of Dyer et al. (2023) for providing the data on patent disclosure quality. The sample for patent disclosure quality proxies is limited to patents filed in the years from 2008 to 2013 due to data availability.

Table 7: Patent disclosure characteristics under IP litigation

This table presents OLS regressions of patent disclosure characteristics as a function of closed and current IP litigation. Panel A reports results for the effect of current and closed IP litigation. Panel B disaggregates IP litigation into same and different technologies litigated. Same technology is measured when filed and litigated patents are from the same US patent class. I measure patent disclosure characteristics using the patent disclosure quality database of Dyer et al. (2023). All other variables are defined in Appendix A. All models include controls which are not reported for brevity, as well as industry (Fama-French 48) and interacted patent class with filing year fixed effects (Patent Class*Year FE). Standard errors are reported in round parentheses below each coefficient estimate, with standard errors clustered by industry. The ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The period of observation is from 2008 to 2013 (totaling 94,065 patent observations).

Panel A: IP litigation on patent disclosure characteristics

Dependent Var.	*Ln (File Size)*	*Ln (Number Figures)*	*Ln (Number of words)*	*-Ln (FOG Index)*	*Ln (Specificity)*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
IP_litigation	-0.002	-0.010	0.037*	-0.003	-0.052***
	(0.015)	(0.025)	(0.020)	(0.004)	(0.014)
Closed_IP_litigation	0.043**	0.037*	0.052**	0.008*	0.016
	(0.019)	(0.019)	(0.025)	(0.004)	(0.025)
Controls	Yes	Yes	Yes	Yes	Yes
Patent Class*Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	94,065	94,065	94,065	94,065	94,065
Adjusted-R^2	0.253	0.390	0.269	0.111	0.365

Panel B: Same technology litigated and patent disclosure characteristics

Dependent Var.	*Ln (File Size)*	*Ln (Number Figures)*	*Ln (Number of words)*	*-Ln (FOG Index)*	*Ln (Specificity)*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
Same_Tech_Litigated	-0.011	-0.022	0.041**	-0.002	-0.086***
	(0.018)	(0.019)	(0.019)	(0.006)	(0.030)
Same_Tech_Closed	0.087***	0.061*	0.092***	0.009*	0.039
	(0.024)	(0.036)	(0.022)	(0.005)	(0.047)
Different_Tech_Litigated	-0.002	-0.009	0.034	-0.004	-0.045***
	(0.016)	(0.026)	(0.021)	(0.004)	(0.011)
Different_Tech_Closed	0.035	0.034*	0.042	0.008**	0.016
	(0.021)	(0.019)	(0.027)	(0.004)	(0.019)
Controls	Yes	Yes	Yes	Yes	Yes
Patent Class*Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	94,065	94,065	94,065	94,065	94,065
Adjusted-R^2	0.253	0.390	0.269	0.111	0.365

Table 7, Panel A, reports results for the effect of current and closed IP litigation on the disclosure quality of patents. While I find no evidence that current IP litigation affects the disclosure quality of patents for three out of five disclosure quality measures, I find evidence that past IP litigation increases the disclosure quality of patents for four out of five disclosure proxies. In particular, patent descriptions after closed IP litigation cases become longer (larger file sizes and more words) and provide more figures. Additionally, patents after closed IP litigation become easier to read indicated by lower FOG indices.[10] This evidence suggests that patent disclosures after settled IP lawsuits not only become faster, but also more informative.

Next, I investigate whether the effect can be explained by technologically related patents. Panel B reports the results for the disaggregation into same and different technology patents based on their patent class classification. Consistent with my previous results, the effects for same technology patents are economically larger than for unrelated technology patents. Thus, firms increase patent disclosures for the same technologies rather than the unrelated technologies. In sum, IP litigation can also affect the disclosure quality of patents in form of longer texts and figures. Thus, closed IP litigation also has positive externalities on the quality of patent disclosures in form of more detailed patent disclosures.

5.3 Robustness checks

Lastly, I investigate the robustness of my results using two different specifications. First, I split my sample in a pre- and post-period around the Leahy-Smith Invents Act (LSIA) in 2011. The Leahy-Smith America Invents Act was a recent U.S. patent reform, which altered the disclosure requirements in the patent application process.[11] In particular, the LSIA reduced the enforcement

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[10] For easier interpretation of my results, I regress the negative natural logarithm of FOG indices on IP litigation proxies.

[11] Additionally, the Leahy-Smith Invents Act of 2011 also changed the US-patent system from a first to invent to a first to file patent system. For more information on the changes to the patent system, see Rantanen et al. (2011) and Sohi (2013).

about the requirement to disclose all necessary information to be able to reproduce the patent successfully.[12]

Table 8, Panel A, reports results of a sample split among the pre- and post-LSIA period. Again, I find evidence for delayed IP disclosure under IP litigation and accelerated IP disclosure after closed IP litigation in both periods. More importantly, I find that the difference between the coefficients of both periods is statistically insignificant. Thus, the effect of IP litigation on IP disclosure has not been affected by recent changes in disclosure requirements.

Second, I investigate the relation of IP disclosure to another form of litigation risk: class action lawsuits. A potential explanation of my results might be that altered IP disclosures can be explained by a litigious environment rather than underlying IP litigation. Other forms of litigation like the appearance of class action lawsuits might explain the altered IP disclosure behavior as firms are more cautious in those environments (Kempf and Spalt 2023). Using the industry-defined litigation proxy of Francis et al. (1994), I find no associations between *Litigation_environment* and patent disclosures, as reported in Table 8, Panel B. This evidence is inconsistent with the explanation that litigious environments explain differing patent disclosures.

[12] Before the LSIA, a non-disclosure of necessary information would have resulted in an invalidity of the patent. After the LSIA, a non-compliance with this rule does not automatically lead to an invalidation of the patent, which dilutes patent disclosure regulation. Thus, the LSIA might have affected the patent disclosure practices of firms.

Table 8: Robustness tests

This table presents OLS regressions of patent disclosures in different robustness settings. Panel A reports results of a sample split between the pre- and post-period around the Leahy-Smith Invents Acts of 2011. Panel B reports results of another litigation proxy, *Litigation_environment*. I define *Litigation_environment* using the Francis et al. (1994) industry measure. All other variables are defined in Appendix A. All models include controls, which are not reported for brevity, as well as industry (Fama-French 48) and interacted patent class with filing year fixed effects (Patent Class*Year FE). Standard errors are reported in round parentheses below each coefficient estimate, with standard errors clustered by industry. The ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The period of observation is from 2003 to 2013 (totaling 400,725 observations).

Panel A: Leahy-Smith Invents Act

Dependent Var.	*Ln (Days to Disclosure)*		
	Pre-Period	*Post-Period*	*Difference*
	(1)	*(2)*	
IP_litigation	0.763***	0.750***	0.012
	(0.095)	(0.088)	(0.622)
Closed_IP_litigation	-0.408***	-0.435***	0.027
	(0.072)	(0.063)	(0.418)
Controls	Yes	Yes	
Patent Class*Year FE	Yes	Yes	
Industry FE	Yes	Yes	
Observations	306,129	94,596	
Adjusted-R^2	0.226	0.213	

Panel B: Litigation environment

Dependent Var.	*Ln (Days to Disclosure)*	*Percentage Disclosure Delay*	*Disclosure 30 Days before Deadline*
	(1)	*(2)*	*(3)*
Litigation_environment	-0.061	-0.007	0.003
	(0.123)	(0.043)	(0.068)
Controls	Yes	Yes	Yes
Patent Class*Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	400,725	400,725	400,725
Adjusted-R^2	0.183	0.125	0.141

6. Conclusion

In this paper, I examine the effect of IP litigation on IP disclosure. Using patent disclosures as the unit of observation, I find that current IP litigation delays the disclosure of innovation, while closed IP litigation accelerates the disclosure. This evidence is consistent with firms delaying IP disclosures under IP uncertainty and accelerating IP disclosures when IP uncertainty is resolved. Patent disclosure quality even improves after the settlement of IP lawsuits. Difference-in differences estimations around the Supreme Court trial of *eBay vs. MercExchange* in 2006 provide additional evidence that when current IP litigation risks for computer & communication patents (lower injunction likelihood) are lowered, firms accelerate the timing of patent disclosures for this technology class in comparison to patents from other technological fields. Additionally, plaintiff-friendly IP courts contribute to those observed disclosure effects.

My paper contributes to the regulatory debate on the potential externalities of rising IP litigation on the disclosure of innovation. Several academics have raised negative concerns about the growing concerns of IP litigation. In this paper, I document both negative and positive effects of IP litigation on the IP disclosure of firms providing a new perspective to the debate of rising IP litigation and patent enforcement.

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Appendix A: Variable definitions

Variable	Definition	Source
Dependent variables:		
Ln (Days to Disclosure)	The number of days until the USPTO publishes a patent filing, either at the request of the applicant or because the disclosure deadline passes, less 14 weeks for publication delays. It is defined on patent level (Glaeser and Landsman 2021)	USPTO examination research database
Percentage Disclosure Delay	The number of days until the disclosure of a patent filing, divided by the number of days until the latest possible disclosure. It is defined on patent level (Glaeser and Landsman 2021).	USPTO examination research database
Disclosure 30 Days before Deadline	Indicator variable equal to one if patent is disclosed 30 days before the deadline, zero otherwise. It is defined on patent level.	USPTO examination research database
Ln (File Size)	Natural logarithm of a patent file size in bytes.	Dyer et al. (2023)
Ln (Number Figures)	Natural logarithm of the number of figures included in the patent.	Dyer et al. (2023)
Ln (Number of words)	Natural logarithm of the number of words in the written description portion of the patent.	Dyer et al. (2023)
-Ln (FOG Index)	Negative natural logarithm of the Gunning (1952) FOG Index of the patent.	Dyer et al. (2023)
Ln (Specificity)	Natural logarithm of the number of specific pieces of information (quantities, percentages, names) identified in the written description portion of the patent.	Dyer et al. (2023)
IP litigation variables:		
IP_litigation	Indicator variable equal to one if a firm faces a patent lawsuit in the disclosure process of a patent, zero otherwise.	USPTO litigation docket reports database
Closed_IP_litigation	Indicator variable equal to one if a firm closed a patent lawsuit one year before the filing of a patent, zero otherwise.	USPTO litigation docket reports database
Same_Tech_Litigated	Indicator variable equal to one if a filed patent is from the same patent class than the litigated patent, zero otherwise. It is identified within current IP litigation.	USPTO examination research database
Same_Tech_Closed	Indicator variable equal to one if a filed patent is from the same patent class than the litigated patent, zero otherwise. It is identified within closed IP litigation.	USPTO examination research database
Different_Tech_Litigated	Indicator variable equal to one if a filed patent is from a different patent class than the litigated patent, zero otherwise. It is identified within current IP litigation.	USPTO examination research database
Different_Tech_Closed	Indicator variable equal to one, if a filed patent is from a different patent class than the litigated patent, zero otherwise. It is identified within closed IP litigation.	USPTO examination research database

Ln(1+IP lawsuit number)	Natural logarithm of the number of filed IP lawsuits in the disclosure process of a patent.	USPTO litigation docket reports database
Ln (1+ litigated patents)	Natural logarithm of the number of patents currently under litigation.	USPTO litigation docket reports database
Valuable_Patent_litigated	Indicator variable equal to one, if a valuable patent is litigated, zero otherwise. I measure valuable patents using the Kogan et al. (2017) database. Valuable patents is equal to one if the market value of the litigated patent is above the median of all litigated patents, zero otherwise.	USPTO litigation docket reports database / Kogan et al. (2017)
Negative_IP_Reaction	Indicator variable equal to one if a patent is filed under a lawsuit with a severe negative capital market reaction, zero otherwise. I measure a severe capital market reaction using the capital market reaction around the filing of the IP lawsuit using a market model around a three day event window [-1,+1].	USPTO litigation docket reports database/ CRSP
Late_Disc_IP_litigation	Indicator variable equal to one, if a patent is filed under current IP litigation and the patent disclosure decision is late, zero otherwise. I measure late disclosure when the disclosure delay is in 75th percentile of the distribution of the variable *Ln (Days to Disclosure)*.	USPTO litigation docket reports database
Early_Disc_IP_litigation	Indicator variable equal to one, if a patent is filed under current IP litigation and the patent disclosure decision is early, zero otherwise. I measure late disclosure when the disclosure delay is in 25th percentile of the distribution of the variable *Ln (Days to Disclosure)*.	USPTO litigation docket reports database
Late_Disc_closed_IP_litigation	Indicator variable equal to one, if a patent is filed under closed IP litigation and the patent disclosure decision is late, zero otherwise. I measure late disclosure when the disclosure delay is in 75th percentile of the distribution of the variable *Ln (Days to Disclosure)*.	USPTO litigation docket reports database
Early_Disc_closed_IP_litigation	Indicator variable equal to one, if a patent is filed under closed IP litigation and the patent disclosure decision is early, zero otherwise. I measure late disclosure when the disclosure delay is in 25th percentile of the distribution of the variable *Ln (Days to Disclosure)*.	USPTO litigation docket reports database
ICT_Patent	An indicator variable equal to one if the patent is assigned to the “computer & communications” industry category, zero otherwise. I define the computer industry category using the NBER patent classification following Hall et al. (2001).	USPTO examination research database
Post	Indicator equal to one, if a patent has been filed after the *eBay vs. MercExchange* lawsuit, zero otherwise. The case was closed in the second quarter of 2006, i.e. on May 30th, 2006.	USPTO examination research database
EDT_Exposure	Indicator variable equal to one, if a firm has high exposure to IP lawsuits in the Eastern District of Texas (EDT), zero otherwise. I measure exposure by the fraction of the number IP lawsuits faced in EDT to total IP lawsuits. Exposure is high when the fraction is above the median.	USPTO litigation docket reports database

EDT_Non_Exposure	Indicator variable equal to one, if a firm does not have high exposure to IP lawsuits in the Eastern District of Texas, zero otherwise.	USPTO litigation docket reports database
Litigation_environment	Indicator variable equal to one for high litigation risk industries, zero otherwise, as defined in Francis et al. (1994).	Compustat

Control variables:

HHI	The natural logarithm of the sum of the squared market share of each publicly traded firm in a particular four-digit SIC code in a given year. Market share is calculated as the sales of a particular firm divided by the total Compustat sales of the SIC code.	Compustat
Fluidity	Measure captures how rivals are changing the product words that overlap with firm i's vocabulary. Thus, it captures product market threats in a specific industry segment.	Hoberg et al. (2014)
Loss	Indicator variable equal to one if net income is negative, zero otherwise.	Compustat
ROA	Income before extraordinary items divided by total assets.	Compustat
R&D	R&D expenditures scaled by total assets. Missing values of research & development expenditures are replaced with zeroes.	Compustat
Missing R&D	Indicator variable equal to one if firm has missing research & development expenditures, zero otherwise (Koh and Reeb 2015).	Compustat
Leverage	Sum of short-term debt and long-term debt scaled by total assets.	Compustat
External Capital Dependence	Capital expenditures plus R&D expenditures minus operating activities net cash flow, divided by capital expenditures plus R&D expenditures (Rajan and Zingales 1998).	Compustat
Cash	Cash and cash equivalents divided by total assets.	Compustat
Size	Natural logarithm of total assets.	Compustat
Market-to-Book	Market value of equity divided by common shareholder equity.	Compustat/ CRSP
Number Cites	The natural logarithm of 1 plus the number of citations the patent receives from subsequent patents.	Kogan et al. (2017)
Patent_Value	The natural logarithm of the patent value estimated with the capital market reaction around the granting date.	Kogan et al. (2017)
Breadth	The natural logarithm of the technological breadth of a patent. It indicates whether a patent can also be used in other patent categories using the description section of a patent. For more details on the variable construction, see Bowen et al. (2023).	Bowen et al. (2023)
ln(Possible Disclosure)	The number of days until the patent application must be published (for applications seeking foreign protection, the earlier of 18 months after filing abroad and the patent decision date, and for all others, the application decision date) (Glaeser and Landsman 2021).	USPTO examination research database

Appendix B: Patent disclosure of Biogen Inc.

This appendix presents the cover page of the patent number 9506867 filed by Biogen Inc. The patent was filed with the USPTO on December 11th, 2013 and granted on November 29th, 2016. Biogen Inc. decided to disclose the patent on July 3rd, 2014.

US009506867B2

(12) **United States Patent**
Moretto et al.

(10) **Patent No.: US 9,506,867 B2**
(45) **Date of Patent: Nov. 29, 2016**

(54) **SPECTROSCOPIC ANALYSIS OF NUTRIENT MATERIALS FOR USE IN A CELL CULTURE PROCESS**

(71) Applicant: **Biogen MA Inc.**, Cambridge, MA (US)

(72) Inventors: **Justin Moretto**, Apex, NC (US); **Kelly Wiltberger**, Cary, NC (US)

(73) Assignee: **Biogen MA Inc.**, Cambridge, MA (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 69 days.

(21) Appl. No.: **14/103,801**

(22) Filed: **Dec. 11, 2013**

(65) **Prior Publication Data**

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G01N 21/65 (2006.01)

(52) **U.S. Cl.**
CPC ***G01N 21/65*** (2013.01); ***G01J 3/44*** (2013.01)

(58) **Field of Classification Search**
CPC G01J 3/44; G01N 21/65
See application file for complete search history.

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(Continued)

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(57) **ABSTRACT**

In some embodiments, aspects of the disclosure relate to methods of evaluating cell culture materials, for example, nutrient materials, or other materials that can be used in cell culture media.

14 Claims, 5 Drawing Sheets

Appendix C: Robustness tests patent disclosure delays under IP litigation

This table presents robustness tests of baseline OLS regressions of patent disclosure as a function of closed and current IP litigation presented in Table 2. Panel A estimates Table 2 without the pharmaceutical industry, while Panel B estimates Table 2 with firm- instead of industry fixed effects. Panel C estimates the effects without the two major industries "Business Services" & "Electronic Equipment", while Panel D estimates the effects within those two industries. All other variables are defined in Appendix A. All models include controls, which are not reported for brevity, as well as interacted patent class with filing year fixed effects (Patent Class*Year FE). Standard errors are reported in round parentheses below each coefficient estimate, with standard errors clustered by industry. The ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The period of observation is from 2003 to 2013 (totaling 400,725 observations).

Panel A: Pharmaceutical industry excluded

Dependent Var.	*Ln (Days to Disclosure)*	*Percentage Disclosure Delay*	*Disclosure 30 Days before Deadline*
	(1)	*(2)*	*(3)*
IP_litigation	0.768***	0.233***	0.291***
	(0.089)	(0.023)	(0.028)
Closed_IP_litigation	-0.422***	-0.126***	-0.158***
	(0.070)	(0.017)	(0.022)
Controls	Yes	Yes	Yes
Patent Class*Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	386,010	386,010	386,010
Adjusted-R^2	0.212	0.165	0.159

Panel B: Firm fixed effects

Dependent Var.	*Ln (Days to Disclosure)*	*Percentage Disclosure Delay*	*Disclosure 30 Days before Deadline*
	(1)	*(2)*	*(3)*
IP_litigation	0.982***	0.298***	0.363***
	(0.084)	(0.020)	(0.028)
Closed_IP_litigation	-0.076**	-0.018**	-0.020**
	(0.028)	(0.007)	(0.009)
Controls	Yes	Yes	Yes
Patent Class*Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	400,725	400,725	400,725
Adjusted-R^2	0.273	0.239	0.239

Panel C: Business Services & Electronic Equipment industries excluded

Dependent Var.	*Ln (Days to Disclosure)*	*Percentage Disclosure Delay*	*Disclosure 30 Days before Deadline*
	(1)	*(2)*	*(3)*
IP_litigation	0.636***	0.208***	0.253***
	(0.069)	(0.022)	(0.034)
Closed_IP_litigation	-0.311***	-0.100***	-0.125***
	(0.052)	(0.017)	(0.022)
Controls	Yes	Yes	Yes
Patent Class*Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	201,970	201,970	201,970
Adjusted-R^2	0.296	0.218	0.222

Panel D: Business Services & Electronic Equipment industries only

Dependent Var.	*Ln (Days to Disclosure)*	*Percentage Disclosure Delay*	*Disclosure 30 Days before Deadline*
	(1)	*(2)*	*(3)*
IP_litigation	0.964**	0.275**	0.339**
	(0.061)	(0.019)	(0.018)
Closed_IP_litigation	-0.577**	-0.166***	-0.208**
	(0.010)	(0.001)	(0.006)
Controls	Yes	Yes	Yes
Patent Class*Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	198,755	198,755	198,755
Adjusted-R^2	0.169	0.143	0.132

Appendix D1: Growth vs. mature firms

This table presents OLS regressions of patent disclosures as a function of IP litigation risk conditional being a growth or mature firm using sample splits. I use the cash flow statement classification of Dickinson (2011) and Vorst and Yohn (2018) to separate firms into growth and mature firms. All variables are defined in Appendix A. All models include controls which are not reported for brevity, as well as industry (Fama-French 48) and interacted patent class with filing year fixed effects (Patent Class*Year FE). Standard errors are reported in round parentheses below each coefficient estimate, with standard errors clustered by industry. The ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The period of observation is from 2003 to 2013 (totaling 400,725 observations).

Dependent Var.	*Ln (Days to Disclosure)*			*Percentage Disclosure Delay*			*Disclosure 30 Days before Deadline*		
	Growth Firms	Mature Firms	Difference	Growth Firms	Mature Firms	Difference	Growth Firms	Mature Firms	Difference
	(1)	*(2)*		*(3)*	*(4)*		*(5)*	*(6)*	
IP_litigation	0.952***	0.742***	0.210**	0.281***	0.229***	0.051**	0.345***	0.282***	0.062**
	(0.135)	(0.068)	(0.035)	(0.035)	(0.016)	(0.043)	(0.040)	(0.024)	(0.036)
Closed_IP_litigation	-0.408***	-0.401***	0.007	-0.113***	-0.122***	-0.009	-0.135***	-0.152***	-0.017
	(0.074)	(0.057)	(0.817)	(0.017)	(0.015)	(0.383)	(0.024)	(0.021)	(0.473)
Controls	Yes	Yes		Yes	Yes		Yes	Yes	
Patent Class*Year FE	Yes	Yes		Yes	Yes		Yes	Yes	
Industry FE	Yes	Yes		Yes	Yes		Yes	Yes	
Observations	82,165	318,158		82,165	318,158		82,165	318,158	
Adjusted-R^2	0.256	0.225		0.222	0.172		0.203	0.176	

Appendix D2: Origination versus continuation patents

This table presents OLS regressions of patent disclosures as a function of IP litigation risk conditional on being an origination or continuation patent using sample splits. All variables are defined in Appendix A. All models include controls which are not reported for brevity, as well as industry (Fama-French 48) and interacted patent class with filing year fixed effects (Patent Class*Year FE). Standard errors are reported in round parentheses below each coefficient estimate, with standard errors clustered by industry. The ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The period of observation is from 2003 to 2013 (totaling 400,725 observations).

Dependent Var.	*Ln (Days to Disclosure)*			*Percentage Disclosure Delay*			*Disclosure 30 Days before Deadline*		
	Original Patent	Contin. Patent	Difference	Original Patent	Contin. Patent	Difference	Original Patent	Contin. Patent	Difference
	(1)	*(2)*		*(3)*	*(4)*		*(5)*	*(6)*	
IP litigation	0.150***	0.538***	0.388***	0.060***	0.184***	0.124***	0.090***	0.128***	0.038
	(0.026)	(0.044)	(0.000)	(0.010)	(0.014)	(0.000)	(0.015)	(0.027)	(0.321)
Closed_IP_litigation	-0.081***	-0.262***	-0.181***	-0.030**	-0.092***	-0.063***	-0.046**	-0.080***	-0.034
	(0.028)	(0.054)	(0.000)	(0.013)	(0.017)	(0.000)	(0.020)	(0.027)	(0.403)
Controls	Yes	Yes		Yes	Yes		Yes	Yes	
Patent Class*Year FE	Yes	Yes		Yes	Yes		Yes	Yes	
Industry FE	Yes	Yes		Yes	Yes		Yes	Yes	
Observations	209,931	190,295		209,931	190,295		209,931	190,295	
Adjusted-R^2	0.103	0.463		0.106	0.171		0.010	0.104	