Accounting for Intangibles: The Role of Capitalized R&D in Explaining Market Value

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Abstract – English

Title: Accounting for Intangibles: The Role of Capitalized R&D in Explaining Market Value

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This study investigates whether capitalizing research and development (R&D) expenditures enhances the value relevance of financial information in U.S. capital markets. While R&D is a key driver of firm innovation and long-term value, it is typically expensed under U.S. GAAP, limiting its visibility in financial statements. A standardized capitalization and amortization approach is applied to firm-level R&D data to assess its impact on the explanatory power of earnings–price regressions. Based on a panel of U.S. firms from 1994 to 2023, the analysis shows that capitalizing R&D consistently increases the informativeness of reported earnings, particularly in more recent years. The findings indicate that markets increasingly price R&D as an unrecognized asset and that failing to account for it distorts valuation signals. These findings contribute to ongoing debates in financial reporting and intangible valuation by providing long-run empirical evidence on the effects of R&D capitalization on the capital market. The results have implications for analysts, investors, and accounting standard setters, highlighting the need for more transparent treatment of intangible-related expenditures in financial reporting.

Keywords: R&D capitalization, value relevance, intangible assets, financial reporting, earnings–price regression, intangible valuation

Resumo – Português

Titulo: Contabilização de activos incorpóreos: O papel da I&D capitalizada na explicação do valor de mercado

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Este estudo investiga se a capitalização das despesas com investigação e desenvolvimento (I&D) aumenta a relevância informativa da informação financeira nos mercados de capitais dos EUA. Embora a I&D seja um motor fundamental da inovação empresarial e do valor a longo prazo, é normalmente reconhecida como gasto corrente ao abrigo dos princípios contabilísticos geralmente aceites nos EUA (US GAAP), o que limita a sua visibilidade nas demonstrações financeiras. É aplicada uma abordagem padronizada de capitalização e amortização aos dados de I&D a nível empresarial para avaliar o seu impacto na capacidade explicativa das regressões entre resultados e preços. Com base num painel de empresas norte-americanas entre 1994 e 2023, a análise mostra que a capitalização da I&D aumenta consistentemente a capacidade informativa dos resultados reportados, especialmente nos anos mais recentes. Os resultados indicam que os mercados valorizam cada vez mais a I&D como um ativo não reconhecido, e que a sua não contabilização distorce os sinais de avaliação. Estas conclusões contribuem para os debates em curso sobre relato financeiro e valorização de intangíveis, fornecendo evidência empírica de longo prazo sobre os efeitos da capitalização da I&D no mercado de capitais. Os resultados têm implicações para analistas, investidores e normalizadores contabilísticos, sublinhando a necessidade de um tratamento mais transparente das despesas relacionadas com intangíveis no relato financeiro.

Palavras-chave: capitalização de R&D, relevância informativa, ativos intangíveis, relato financeiro, regressão resultados–preço, valorização de intangíveis

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1 Introduction

The role of intangibles in firm valuation and the limitations of financial reporting in capturing their economic significance have become an increasingly central challenge in accounting and capital market research. A growing body of literature has documented the structural economic shift toward intangible-intensive business models, marked by an increasing dominance of R&D, software, and knowledge. While research and development (R&D) expenditures are central to this transition, prevailing accounting standards treat them mainly as period costs, particularly under U.S. GAAP. This treatment fails to recognize their potential long-term economic benefits and limits their visibility in financial statements.

Financial reporting continues to rely on accounting frameworks developed during the industrial era, despite growing evidence that they no longer reflect the primary value drivers of modern firms. Numerous studies have shown persistent and widening market-to-book disparities, declining value relevance of earnings, and the increasing dominance of intangibles in shaping firm performance (Lev, 2003; Peters & Taylor, 2017; Eisfeldt & Papanikolaou, 2013). These trends have raised concerns about financial statements' informativeness and ability to support efficient capital allocation in increasingly intangible-driven markets.

Early empirical work, most notably Sougiannis (1994) and Lev and Sougiannis (1996), demonstrated that capitalizing R&D expenditures, rather than expensing them, can improve the explanatory power of firm-specific financial information on market values. Their findings provided a foundation for subsequent research on the treatment of intangibles. Nevertheless, many follow-up studies have been limited in scope, often focusing on short time windows or sector-specific samples. As a result, important questions remain about whether the positive valuation effects of R&D capitalization persist. In particular, it remains unclear whether capitalizing R&D enhances the informational content of earnings in a consistent, robust manner across decades of structural economic transition.

This study contributes to that conversation by investigating whether capitalizing R&D expenses enhances the value relevance of financial information in U.S. capital markets and how this relationship evolves over time. Drawing on the methodological foundation established by Lev and Sougiannis (1996), it applies a standardized capitalization and amortization framework to firm R&D data over a 30-year period, from 1994 to 2023. It finds that capitalizing R&D consistently increases the explanatory power of price–earnings regressions, particularly in more recent periods. The results suggest that, as intangible investment becomes more central to firm strategy and investor focus, the informational contribution of capitalized R&D also intensifies.

These findings have both theoretical and practical significance. For analysts and investors, they highlight that adjusting for expensed R&D can materially improve valuation accuracy. For accounting standard setters, the results suggest that current expensing rules understate firm value over various industries and deserve reconsideration. More broadly, this thesis supports the view that accounting systems must evolve to better reflect the economic reality of modern firms, and that even partial capitalization of intangible-related expenditures may improve the usefulness of reported financial information in capital market decisions.

2 Theoretical Framework

2.1 Intangibles

2.1.1 Definition of Intangibles

The shift towards a more intangible economy does not simply impact the measurement of individual firms' balance sheets or increase mismatches between these intangibles' book and market values. Moreover, intangibles, as a whole, show significant differences in their economic characteristics from tangible assets that traditionally predominated. (Haskel & Westlake, 2018).

However, despite their considerable economic significance, there is no generally accepted definition of intangibles (Garanina et al., 2021). Intangibles are broadly defined in literature as incorporating various non-physical assets critical to organizational performance and financial evaluation. Intangibles occur in several forms, including intellectual capital, goodwill, brand reputation, and customer relationships.

Intangibles are generally understood as non-physical resources that contribute to value generation within organizations. Cañibano, Covarsí, and Sánchez (1999) define them as potential assets or liabilities, i.e., sources of expected future economic benefits or detriments. The definition highlights the complexity of incorporating them into conventional financial reporting frameworks.

This complexity is also addressed in international accounting standards. According to IAS (International Accounting Standard) 38 (International Accounting Standards Board, 1998), intangible assets must be identifiable, non-monetary, and lack physical substance, while also being controlled by the entity and expected to generate future economic benefits. Further elaborating on these attributes, the IASB (International Accounting Standards Board) distinguishes identifiable intangible assets from unidentifiable goodwill, addressed under International IFRS (International Financial Reporting Standards) 3 and developed as part of the disclosures on business combinations (International Accounting Standards Board, 2004). For an intangible asset to be considered identifiable, it must be separable or arise from contractual or other legal rights. However, many critical intangible resources, such as internally developed brand equity, corporate culture, or in-house knowledge systems, do not meet these formal recognition criteria and are thus excluded from balance sheets (Pastor et al., 2017).

Similarly, the US Financial Accounting Standards Board (FASB) defines intangible assets under ASC (Accounting Standards Codification) 350 (Financial Accounting Standards Board, 2021a). It recognizes them only when they are acquired, either individually or through business combinations (FASB, 2024). Like IAS 38, ASC 350 requires that intangible assets be identifiable, either separable or arising from contractual or legal rights. It does not permit the recognition of most internally generated intangibles. As a result, assets such as internally developed brands, proprietary knowledge, or organizational culture remain unrecognized, reinforcing the conservative, reliability-focused approach shared by both standard-setters.

The recognition criteria employed by most standard-setting bodies remain highly restrictive, placing greater emphasis on reliability than on relevance (Brennan, 2001). As a result, many assets that fall within the broader definition of intangible assets fail to meet the threshold for recognition on corporate balance sheets (Lev, 2001). The approach leaves out numerous internally generated intangibles, such as proprietary processes, brand equity, or organizational know-how, which, while critical to value creation, are not captured within the accounting frameworks.

The term *intellectual capital* has emerged as a broader framework for understanding value creation in knowledge-based economies. Edvinsson and Malone (1999) provide an influential and frequently cited definition, describing intellectual capital as the totality of an organization's collective knowledge, information, intellectual property, experience, and competencies, all of which can be leveraged to create sustained economic value.

Despite these distinctions proposed, significant terminological ambiguity persists in the literature. Authors, including Joia (2000), Lev (2001), and Bontis (2001a), often use the terms *intangible assets, intellectual capital*, and *knowledge assets* interchangeably. Similarly, Mouritsen (2003) emphasizes that these terminologies are used across various academic and professional domains, including accounting, economics, management, and law, highlighting the conceptual fluidity of the field. Lev (2001) notes that accounting scholars tend to favor *intangible assets*, human resources researchers prefer *intellectual capital*, and economists frequently refer to *knowledge assets*.

This view is echoed by Andriessen (2004), who narrows his definition of *intangible resources* down to the meaning of the adjective intangible, meaning unable to be touched or just not tangible. He adds complementary notions such as intangible investments, intangible capital, or intangible assets. Sánchez et al. (2001) reinforce this perspective by using the terms intellectual capital, intangibles, and intangible assets interchangeably, arguing that all describe resources that support innovation and sustainable value generation.

This work adopts Lev's (2001) approach, treating these terminologies as equivalent and focusing specifically on the implications of internally generated intangibles, those critical yet unrecognized drivers of organizational value that are not captured in formal financial statements.

2.1.2 Classification of Intangibles

Given the lack of a universally accepted definition, researchers have proposed various classification frameworks to better conceptualize intangibles and their role in value creation. These classifications typically group intangibles based on their economic function, origin, or relationship to firm infrastructure.

One classification is proposed by Wyatt (2008), who distinguishes between three categories of intangible resources:

- **Technology resources**: including R&D expenditures and associated intellectual property;
- **Human resources**: such as employee skills and expertise;
- **Production resources**: including brands, customer loyalty, and competitive advantages like goodwill.

Lev (2001) offers a related but more detailed framework classifying intangibles into four key categories:

- **Human resources**: employee knowledge and skills;
- **Customer-related intangibles**: including brands and trademarks;
- **Organizational capital**: covering business processes, corporate culture, and internal structure;
- **Discovery-based intangibles**: such as R&D investments;

A more finance-oriented classification comes from Peters and Taylor (2017), who divide intangible capital into:

- **Knowledge capital** (proxied by R&D expenditures);
- **Organizational capital** (proxied by SG&A expenses);

This categorization has empirical appeal, as it maps directly to financial data and supports modeling firm value using measurable inputs.

Alongside these taxonomies, a substantial body of literature has emerged focusing on the previously introduced idea of *intellectual capital*, which serves as a broader framework. Edvinsson and Malone (1999) provide one of the foundational models. Their structure divides it into:

- **Human Capital**: knowledge, skills, and innovative capacities intrinsic to employees;
- **Structural Capital**: internal routines, processes, systems, technologies, and intellectual property;
- **Relational Capital**: value derived from external relationships, such as customer loyalty, brand strength, and supplier networks.

This tripartite model has seen broad adoption in academic literature. Nahapiet and Ghoshal (1998) highlight the integration of intellectual capital within organizational routines and social frameworks, considering knowledge not merely as an individual resource but as a product of the relational environment where it is developed and shared. Further, Rastogi (2003) and

Mouritsen et al. (2004) argue for an integrated and strategic view of intellectual capital, classifying it as a coordinated system of knowledge-based resources and processes that enable innovation and sustainable competitive advantage. These perspectives support the idea that intellectual capital is not a static store of knowledge but a dynamic, integrated capability closely linked to the functioning and development of organizations.

Another important classification is inherent in the prevailing accounting standards, between acquired and internally generated intangibles. While both IFRS and US GAAP permit the recognition of acquired intangibles purchased during business combinations (Financial Accounting Standards Board, 2021a; International Accounting Standards Board, 2004), they impose strict criteria on recognizing internally developed intangibles. Rizova and Saito (2021) explain that internally developed intangibles are difficult to measure reliably and lack market-based transaction prices, making them incompatible with the conservative financial reporting principles. Córcoles (2010) and Caddy (2000), therefore, distinguish between *visible* intangibles, those formally recognized, and *hidden* intangibles that are strategically relevant but unreported.

2.2 Organizational Capital as a Strategic Intangible

2.2.1 Definition and Conceptualization

Organizational Capital, also known as *Organization Capital*, is a form of intangible capital that reflects the firm-specific systems, structures, routines, and knowledge that enable a company to coordinate its physical and human resources efficiently. Unlike physical or financial capital, organizational capital is non-transferable, often tacit, and embedded in the firm's operations and culture. It represents a distinct production factor responsible for persistent performance differences among firms operating in similar environments (Lev & Radhakrishnan, 2005).

A concise definition comes from Evenson and Westphal (1995), who describe organizational capital as “[…] the knowledge used to combine human skills and physical capital into systems for producing and delivering want-satisfying products” (1995, p. 2237). They identify three major firm attributes that constitute this form of capital: (a) operating capabilities, such as product design systems, engineering processes like just-in-time inventory, input outsourcing, and marketing technologies like online distribution; (b) investment capabilities, including sophisticated project selection methods (e.g., real options), internal personnel training, and financial risk engineering; and (c) innovation capabilities, such as distinctive R&D procedures, organizational learning capacity, collaborative practices, and systems for protecting and monetizing intellectual property. This work majorly sheds light on the latter, i.e., a firm's innovation capabilities.

Lev et al. (2009) reinforce this understanding by describing organizational capital as "[…] the agglomeration of business processes and systems, as well as a unique corporate culture, that enables firms to convert factors of production into output more efficiently than competitors." (Lev et al., 2009, p. 276). Unlike intangibles like patents or software, organizational capital represents firm-specific capabilities that are durable and resistant to imitation.

Organizational capital is thus not merely a collection of routines or managerial know-how but an agglomeration of internal business practices, structures, and incentive systems that enable some firms to extract more value from a given set of tangible and human resources than others (Lev & Radhakrishnan, 2005). These practices are accumulated through firm-specific experience and learning, often emerging informally or implicitly through internal adaptation and experimentation. Drawing from the resource-based view and evolutionary economics, Lev and Radhakrishnan (2005) emphasize that organizational capital includes performance evaluation systems, internal governance mechanisms, compensation structures, knowledge-sharing practices, and other integrative capabilities that are not generally codified or tradable.

Eisfeldt and Papanikolaou (2013) define organizational capital as a "production factor that is embodied in the firm's key talent and has an efficiency that is firm specific" (2013, p. 1365). In their view, organizational capital contributes directly to a firm's cash flow generation and varies across firms in ways that affect asset pricing. Unlike physical capital, which shareholders entirely own, the returns to organizational capital are partially claimed by key personnel, such as managers and engineers, because they embody part of the productive efficiency. In a follow-up paper, Eisfeldt and Papanikolaou (2014) summarize two key features: (i) it is partly firm-specific, and (ii) it is partly embodied in key labor inputs such as managers, engineers, salespeople, and research employees.

Evenson and Westphal (1995) further highlight that what they call *tacitness* and the firm-specific nature of this capital is a significant source of competitive advantage. They point out, that "[…] much of the knowledge about how to perform elementary processes and about how to combine them in efficient systems is tacit, not physically embodied, and neither codified nor readily transferable."(1995, p. 2213)

This understanding is also reflected in the distinction made by scholars regarding where organizational capital resides. Some, such as Jovanovic (1979) and Becker (1994), view it as embodied in employees, highlighting factors like job matching, employee-specific learning, and team-based knowledge. Prescott and Visscher (1980) develop this view further by emphasizing three dimensions: what the firm knows about individual employee abilities, how it improves team dynamics through learning, and how human capital contributes collectively to firm performance.

In contrast, a second perspective treats organizational capital as firm-embodied capital good jointly produced with output and embedded in systems rather than people (Atkeson & Kehoe, 2002). This firm-specific capital cannot be sold or transferred and must be built internally, drawing from frameworks by Arrow (1962), Rosen (1972), and Ericson and Pakes (1995).

Empirical studies confirm organizational capital's material economic impact: it explains a significant portion of the variation in firm market values beyond traditional indicators like assets in place and reported earnings (Lev & Radhakrishnan, 2005), and it is especially prominent in firms with high market-to-book ratios (Corrado et al., 2009). Despite its growing relevance, organizational capital remains underrepresented in accounting practices. Whether analysts and investors overlook it due to its hidden nature remains.

The present work follows, in general, the stated, firm-embodied concept of organizational capital, similar to that of Lev and Radhakrishnan (2005). It especially emphasizes the nature of organizational capital being developed internally.

2.2.2 Strategic and Financial Relevance of Organizational Capital

One of the defining strategic features of organizational capital is its non-tradability. Because it is embedded in internal systems, routines, and culture, it cannot be bought or sold in markets like physical or financial assets. This lack of transferability provides a basis for sustainable competitive advantage (Lev & Radhakrishnan, 2005). Firms that have accumulated efficient coordination, knowledge-sharing, and control systems can generate higher value from similar inputs compared to their peers. As noted by Evenson and Westphal (1995), the tacit, non-codified nature of these systems means they cannot be easily imitated, establishing enduring performance differences even under similar external conditions.

The financial implications of organizational capital have been analyzed extensively in recent years, particularly through its role in cash flow generation and asset pricing. Eisfeldt and Papanikolaou (2013) emphasize that organizational capital is a production factor that contributes directly to a firm’s earnings stream and is partially embodied in key personnel. This hybrid ownership model affects both the valuation and the risk profile of firms, since capital markets price in the dependence on hard-to-replace internal systems and talent.

Empirical research further confirms that organizational capital is associated with higher Tobin’s Q ratios, elevated profitability, and reduced sensitivity to external shocks. For example, firms with strong internal coordination mechanisms and resilient incentive systems show greater agility and continuity during periods of technological or market change (Lev & Radhakrishnan, 2005). These firms tend to outperform others in stable and volatile environments, as their embedded routines provide adaptive capacity without needing constant external investment or restructuring.

Lev et al. (2009) reinforce this point by empirically demonstrating that firms with high levels of organizational capital consistently outperform their peers in future income and sales growth.

Organizational capital is also connected with firm-specific learning processes. According to the evolutionary economics perspective, the routines and knowledge structures that form organizational capital are not static; they evolve over time through adaptation, trial and error, and shared institutional memory (Arrow, 1962). This ongoing accumulation of experience makes organizational capital a strategic asset that supports present-day operations and enables innovation and path-dependent growth.

Because of these strategic features, organizational capital has become increasingly relevant in discussions about the intangible economy. Its strategic and financial importance justifies its inclusion in conceptual models of intangible assets, even though it remains mainly unmeasured and unreported in financial statements.

2.3 The Accounting View on Intangibles

While this study's empirical focus is on US-listed companies, which are thus subject to US GAAP, it provides a comparative overview of both US (FASB) and international (IASB) accounting standards to highlight shared limitations and contextualize the debate on intangible asset recognition.

2.3.1 Principles under IAS/IFRS and U.S. GAAP

IAS 38 (International Accounting Standards Board, 1998) bases the recognition of intangible assets on three key criteria: identifiability, control, and the expectation of future economic benefits. An intangible asset is identifiable if it is separable, i.e., capable of being sold, transferred, licensed, rented, or exchanged, either individually or together with a related contract, asset, or liability. Alternatively, it may be identifiable if it arises from contractual or other legal rights, regardless of whether they are transferable or separable from the entity or other rights and obligations. Control is determined when an entity has the authority to receive future economic benefits from the underlying resource and to limit the access of others to these benefits.

Under ASC 350 (Financial Accounting Standards Board, 2021a), intangible assets are recognized if they are identifiable, meaning they are either separable or arise from contractual or legal rights, consistent with IAS 38. Under US GAAP, most internally generated intangible assets are not recognized on the balance sheet. Instead, FASB generally permits the recognition of intangible assets only when acquired from external transactions, typically as part of a business combination. At this point, they may be recorded as separately identifiable intangibles or subsumed under goodwill (see also ASC 350-20).

2.3.2 Internally Generated vs. Acquired Intangibles

Externally acquired intangible assets typically satisfy the recognition criteria under IAS 38 and ASC 350 because their value is established in a market transaction, often as part of a business combination. This transaction-based measurement provides an observable and reliable cost basis, facilitating recognition on the balance sheet. Conversely, internally generated intangibles, such as internally developed software, proprietary algorithms, brand equity, or organizational know-how, present significant accounting challenges. These arise mainly due to difficulties in demonstrating separability, establishing control, and reliably measuring and isolating costs attributable to the intangible (Wyatt, 2008; Zéghal & Maaloul, 2011).

As a result, most accounting standards require the immediate expensing of internally generated intangibles that do not meet strict recognition criteria. According to the FASB's SFAC 5 (Financial Accounting Standards Board, 2021b) and SFAS 2 (Financial Accounting Standards Board, 1974), the failure to meet the measurability and control criteria results in exclusion from the balance sheet, even when such resources clearly possess long-term economic value.

Consequently, intangibles developed through R&D, training, internal process improvements, and marketing often remain unrecorded, leading to systematic underreporting of asset values in knowledge-intensive firms (Lev, 2001; Canibano et al., 2004).

2.3.3 Accounting for R&D

Under US GAAP, the accounting for R&D expenditures is also governed by SFAS 2 (Financial Accounting Standards Board, 1974), which mandates the immediate expensing of all R&D costs as incurred, based on the rationale that the future economic benefits from such expenditures are highly uncertain and unreliable. The only exception to this rule is found in SFAS 86 (Financial Accounting Standards Board, 1985), which allows capitalization of software development costs, but only once technological feasibility has been demonstrated. Costs incurred after this feasibility milestone and before the software is available for general release are capitalized and amortized. All earlier development activity remains expensed.

This policy, however, introduces inconsistency, as economically similar innovation expenditures receive significantly different accounting treatments depending on whether they relate to software or other R&D projects. As Lev and Zarowin (1999) observe, such inconsistencies undermine the comparability and informativeness of financial statements, especially for innovation-intensive firms.

In contrast, IAS 38 (International Accounting Standards Board, 1998) distinguishes between the research and development phases of R&D activities. Under this framework, research costs must be expensed. However, development costs may be capitalized, provided that the project meets a set of six criteria: (i) technical feasibility, (ii) intention to complete and use or sell the asset, (iii) ability to use or sell the asset, (iv) demonstration of future economic benefits, (v) availability of resources to complete the development, and (vi) reliable measurability of expenditures.

These differing treatments result in systematic underrepresentation of innovation assets in US-based financial reports relative to firms reporting under IFRS, further complicating cross-border comparisons and valuation in capital markets.

2.3.4 Critiques of Restrictive Rules

The current accounting treatment of intangibles has been widely criticized for being overly restrictive, particularly in the recognition of internally generated intangible assets. Both international and U.S. accounting standards require an intangible investment to meet stringent criteria regarding identifiability, control, and future economic benefits before it may be capitalized. These thresholds, however, are so demanding that many economically significant investments remain unrecognized on financial statements (Zéghal & Maaloul, 2011).

Control is a central condition under both IAS 38 (International Accounting Standards Board, 1998) and SFAC 5 (Financial Accounting Standards Board, 2021b). It is defined as the power to derive future benefits from an asset and restrict others from doing so. However, this poses a significant barrier in the case of intangible investments such as employee training or organizational knowledge. As Lev (2001) notes, these resources often fail the control test due to labor mobility and the non-ownership of knowledge, leading to their expensing instead of capitalization.

A second major obstacle is the requirement for a reliable measurement. While externally acquired intangibles often meet this criterion, internally developed assets like software, proprietary processes, and R&D outputs typically cannot. As Upton (2003) emphasizes, this measurement barrier frequently excludes conceptually valid assets from recognition, undermining the principle of faithful representation.

A broader conceptual critique concerns accounting conservatism, which justifies the immediate expensing of intangible investments. Basu (1997) describes this principle as requiring a higher threshold for recognizing gains than losses, which results in asymmetric treatment of value creation and frequently understates earnings and book value in innovation-driven sectors. Lev et al. (2005) argue that this principle fails to reflect the firm's economic position consistently and can result in either conservative or aggressive reporting, depending on the firm's growth phase.

Lev and Zarowin (1999) also raise concerns about the declining relevance of financial statements. Financial reports fail to reflect firms' true value drivers as more economically meaningful resources go unrecognized. This decline in relevance is especially problematic in technology and service-oriented industries, where intangible investments dominate capital formation.

Further criticisms come from Malhotra (2000) and Córcoles (2010), who highlight the exclusion of *hidden* intangibles such as organizational culture, internal knowledge systems, and collaborative capabilities. Often crucial to competitive advantage, these elements are typically subsumed under goodwill during mergers or not accounted for.

Finally, the accounting framework's emphasis on reliability and verifiability over economic relevance leads to a systematic undervaluation of firms rich in intellectual capital. Caddy (2000) distinguishes between intangible and intellectual assets, arguing that the latter's inherent volatility and measurement difficulties make them invisible under existing standards. Yet, these resources are central to value creation in knowledge-based economies.

Several authors advocate adjustments to the current accounting model in light of these criticisms. Lev and Zarowin (1999) propose a shift toward capitalization of intangible investments that have passed technological feasibility thresholds, aligning more closely with economic substance than current conservative standards. Similarly, Mortensen et al. (1997) argue for expanding the accounting model to include non-financial disclosures and adjusting recognition criteria to reflect the value relevance of intangibles. Accounting scholars have thus highlighted the need to modify traditional financial statements to capture the growing importance of intangible resources in firm valuation.

Consequently, the prevailing accounting frameworks are seen as outdated within a changing economic structure. As highlighted in the literature, this raises concerns about the adequacy of reporting standards to inform investors.

2.4 Measuring Intangibles

2.4.1 General Valuation Approaches

Due to the restrictive nature of accounting standards toward recognizing internally generated intangible assets, researchers and practitioners have developed various alternative methods for estimating their value. These methods can broadly be classified into cost-based, market-based, income-based, hybrid approaches, and more advanced modeling techniques. Below is an overview of the most established frameworks for evaluating intangibles.

Cost-Based Approaches. Cost-based approaches estimate the value of an intangible asset by calculating the expenditure necessary to reproduce or replace it. Two variants are commonly applied (Brooking, 1996):

- **Reproduction Cost:** Assumes a hypothetical recreation of the exact same asset under current cost conditions.
- **Replacement Cost:** Estimates the cost of creating a substitute asset with similar utility or output potential.

These methods are generally used when market or income data are unavailable, such as to value training systems, internal software, or employee onboarding programs. However, they have been criticized for ignoring an asset's ability to generate future economic benefits (Lev, 2003).

Market-Based Approaches. Market-based methods determine value by comparing the subject intangible asset to similar assets exchanged in open markets. These include:

- **Comparable Transactions**: Valuation is based on sales or licensing deals involving similar intangibles (e.g., brand valuations, trademark sales).
- **Market Multiples**: Derive value using ratios from public companies with similar intangible asset structures.

However, due to the absence of active markets for many intangible assets, applying the comparable transaction approach is often constrained. Intangibles are frequently highly unique in nature, and unless a transaction involving an identical or highly similar asset has occurred, price comparisons are unlikely to yield meaningful valuation insights. As a result, this method can be challenging to implement in practice (Madhani, 2012).

Income-Based Approaches. Income-based methods determine the present value of future economic benefits expected to flow from the intangible (Grant Thornton International Ltd., 2013). Key models include:

- **Relief-from-Royalty Method**: Estimates the cost saved by owning an intangible instead of licensing it. Common for valuing trademarks and patents.

- **Excess Earnings Method (MEEM)**: Attributes residual income to the intangible after deducting returns to all other identified assets (e.g., physical capital, working capital). This is widely used for customer relationships or brand value.

- **Comparative Income Differential Method (CIDM)**: Compares the profitability of firms with and without the asset, assuming that the performance differential reflects the intangible's value.

- **Discounted Cash Flow (DCF)**: Forecasts expected cash flows generated by the intangible asset over time and discounts them back to present value using an appropriate discount rate.

These methods are widely regarded as robust and theoretically sound, but rely on assumptions regarding future earnings, discount rates, and asset lifespans, which can introduce significant subjectivity (Damodaran, 2009).

Return-Based and Capital Market Proxies. When direct valuation is not feasible, researchers such as Williams (2001) use heuristic methods to estimate the value of intangible assets indirectly:

- **Return on Assets (ROA) Differential**: Measures the firm's profitability over the industry average. The idea is that superior returns are attributable to unrecognized intangible resources.

- **Market Capitalization Approach:** Calculates the difference between a firm's market capitalization and its book value to infer the value of unreported intangibles.

However, multiple variables might influence these values, and do not allow for asset-specific breakdowns towards intangible assets (Verbano & Crema, 2013). As Lev (2018) highlights the widening gap between market and book values, which reflects the growing importance of unrecognized intangibles. This issue encourages deeper investigation into their value relevance, which will be explored in the course of this work.

Hybrid Intellectual Capital Frameworks. These models combine financial valuation techniques with qualitative judgments and structured managerial inputs:

- **FiMIAM (Financial Method of Intangible Assets Measurement)**: Managers allocate company value across various intangible components based on expert input and firm-specific metrics (Rodov & Leliaert, 2002).

- **Inclusive Valuation Methodology (IVM)**: Integrates both quantitative data and strategic indicators, enabling valuation of complex intangibles like corporate culture or knowledge networks (M'Pherson & Pike, 2001).

- **Citation-Weighted Patent Valuation**: This method uses citation metrics to assess the technological significance and market relevance of patent portfolios (Bontis, 2001b).

- **Semi-Qualitative Approaches**: Combine surveys, benchmarking, and expert assessments to derive a subjective valuation score, often used for intellectual capital (Verbano & Crema, 2013).

Real Options and Quantitative Models. Real option models account for managerial flexibility in decision-making under uncertainty and are well-suited for intangibles that involve phased investment (e.g., drug development or software projects):

- **Binomial Trees and Monte Carlo Simulations** are used to model the evolving value of assets with uncertain cash flows or multiple future outcomes (Lagrost et al., 2010).

Despite their theoretical appeal, these methods are rarely used in practice due to high complexity, data needs, and modeling expertise.

2.4.2 Measuring Organizational Capital

Although critical to firm success, organizational capital is not explicitly represented on the balance sheet. As noted previously, most of its associated expenditures, such as investments in IT, internal training, brand development, logistics, and R&D, are expensed as incurred. In addition, measuring organizational capital presents a further significant empirical challenge due to its stated tacit, firm-specific, and internally accumulated nature.

SG&A-Based Approaches. A foundational contribution by Lev and Radhakrishnan (2005) proposes measuring organizational capital through two distinct frameworks. One of these is the SG&A productivity method, in which Selling, General, and Administrative (SG&A) expenses are treated as a proxy for investment in organizational capital. The assumption is that SG&A includes spending on intangible yet value-enhancing activities such as internal training, branding, information systems, and managerial infrastructure. By constructing a firm-level production function and comparing actual versus predicted sales, they isolate a firm's organizational productivity. Higher sales relative to observable inputs suggest greater organizational capital intensity.

Building on this, Eisfeldt and Papanikolaou (2013) adopt a more structured and finance-oriented implementation using the perpetual inventory method. They accumulate deflated SG&A spending over time to construct a stock of organizational capital, assuming a constant depreciation rate (typically 15%) and a firm-specific investment growth rate. This stock is then scaled relative to total assets to form an organization capital-to-asset ratio (O/K), which they use to rank firms and test asset pricing implications.

Further developments include Lev et al. (2009), who extend the SG&A framework to incorporate cost savings in cost of goods sold (COGS) as additional organizational capital contributions. This recognizes efficiencies achieved through improved internal systems, logistics, and managerial innovations.

However, the SG&A approach is not without limitations. Eisfeldt and Papanikolaou (2013) acknowledge that SG&A is a noisy proxy, as not all expenses within that category contribute to organizational capital. Accounting discretion and industry-specific reporting norms can affect comparability. Moreover, while SG&A may capture investment-related spending, it does not measure the effectiveness or durability of the practices and systems being developed.

Residual-Based Approaches. Lev and Radhakrishnan (2005) also propose a residual-based method for estimating organizational capital. Here, firm output is modeled using a Cobb-

Douglas production function that includes physical capital, labor, and R&D capital. The output portion unexplained by these inputs, meaning the residual, is attributed to organizational capital. This method aligns with the tradition of Solow (1957) and Griliches and Mairesse (1995), who treated residual productivity as capturing unobserved efficiency.

However, this approach has been criticized. Abramovitz (1956) referred to such residuals as "a measure of our ignorance," since they may also reflect omitted variables or measurement error. Atkeson and Kehoe (2002) reinforce this view by modeling organizational capital as a firm-specific capital good that is jointly produced with output and embedded in systems rather than people. This theoretical model treats organizational capital as inseparable from firm-specific experience and internal infrastructure, which explains its unobservability and measurement complexity.

Building on this, Atkeson and Kehoe (2005) provide empirical evidence from U.S. manufacturing data, showing that organizational capital accumulates as firms age and contributes significantly to productivity growth. They introduce the concept of "organization rents," reflecting the returns owners earn for investing in firm-specific knowledge and offering a quantifiable measure of the economic value of organizational capital.

Survey and Alternative Approaches. Alternative approaches have also emerged. Survey-based methods such as those by Black and Lynch (2005) and Bloom and Van Reenen (2007) directly capture management practices, training routines, and process standardization through firm-level questionnaires. Black and Lynch (2005) focus on job design, employee voice, and training, while Bloom and Van Reenen (2007) present a comprehensive framework for comparing management practices across firms and countries.

These methods offer rich, contextual insight into organizational structures, However, Lev et al. (2016) note that survey-based methods lack scalability and cross-firm comparability and are vulnerable to self-reporting bias.

Combined Intangible Capital Models. Peters and Taylor (2017) construct a combined intangible capital model using both R&D and SG&A flows. Applying a perpetual inventory approach to both inputs and using industry-specific amortization rates provided by Li and Hall

(2020), they derive knowledge capital from R&D and organizational capital from SG&A to form an intangible capital asset. By aggregating both inputs, they explain firm-level investment behavior using a two-factor Q model.

Further refinements are seen in Rizova and Saito (2021), who integrate SG&A-based organizational capital with R&D-based knowledge capital in their asset pricing analysis. They use amortization methods to transform R&D and SG&A flows into capital stocks, but emphasize the data sparsity and high noise levels in such estimations.

Lev et al. (2009) also emphasize that organizational capital's tacitness is among the main reasons this resource is hard to quantify. Input measures, such as mentoring or internal knowledge sharing, are not systematically tracked in accounting systems. Output measures, such as business design quality, lack market prices and are difficult to isolate from other contributors to performance.

2.5 Value Relevance of Intangibles in Capital Markets

As described in this work, the increasing economic dominance of intangibles, such as R&D, software, brand equity, and organizational know-how, has raised critical questions about the ability of traditional financial statements to reflect firm value.

One of the most frequently cited consequences of failing to recognize intangible assets is the growing divergence between market capitalization and book value. This disconnect has become especially pronounced in knowledge-based industries, where firm value is increasingly driven by internally developed, non-physical assets that remain off-balance, especially under U.S. GAAP.

These concerns are central to the value relevance of accounting information, which is broadly defined as the extent to which financial statement data explains or predicts stock prices, returns, or other market variables (Barth et al., 2001).

2.5.1 Empirical Evidence on the Value Relevance of Intangibles

The declining informativeness of financial statements in the presence of rising intangible investments has led to various empirical studies assessing intangible assets' value relevance. These studies examine the ability of adjusted financial metrics, whether through capitalization proxies, residual estimation, or external adjustments, to explain stock returns, market value, or future performance.

Lev and Zarowin (1999) show that the explanatory power of accounting earnings and book values for market prices declined significantly between 1977 and 1996. They argue that this deterioration coincides with the rise of intangible investment in software, R&D, and human capital, none of which are consistently captured in financial statements. Their work highlights a structural gap between modern firms' economic reality and financial reporting structure.

This concern is reinforced by the empirical study of Ciftci et al. (2014), who examine the value relevance of accounting information in intangible-intensive industries. They find that the value relevance of traditional financial measures (e.g., earnings and book value) is significantly lower in sectors such as healthcare, information technology, and services, compared to tangible-intensive industries like manufacturing or utilities. Notably, the value relevance improves when firm-specific intangibles are proxied using indicators like SG&A intensity and R&D expenditures, further supporting the case for economic adjustments to book value.

Eisfeldt, Kim, and Papanikolaou (2021) show that firms with high intangible value are mispriced in standard models unless intangibles are capitalized. They find that intangibles-adjusted value portfolios outperform traditional value strategies, especially when intangible capital is decomposed into R&D and organizational components. Their work highlights the dual role of intangibles in both valuation and return predictability, suggesting that market participants, whether consciously or not, price in these hidden resources.

Eisfeldt and Papanikolaou (2013) take a different approach by developing an organizational capital index based on SG&A expenditures and validating its economic relevance through asset pricing tests. Firms with high organizational capital earn higher risk-adjusted returns, consistent with the idea that markets recognize, but cannot directly observe, the productivity associated with well-developed internal capabilities.

In a related approach, Peters and Taylor (2017) capitalize R&D and SG&A to estimate organizational. Their investment-Q model shows that intangible-adjusted Tobin’s Q ratios are more predictive of firm performance and investment than traditional Q, reinforcing the idea that financial markets absorb intangible value even if it’s not recorded on the balance sheet.

Similarly, Rizova and Saito (2021) jointly modeling knowledge capital (from R&D) and organizational capital (from SG&A) and showing that their combined capitalization helps explain cross-sectional differences in expected stock returns. Their results indicate that intangible-rich firms are mispriced by traditional accounting-based models, especially when intangibles are omitted from the investment base.

Ewens et al. (2024) use market prices, rather than accounting proxies, to construct intangible-adjusted book values. Their empirical results show that book-to-market ratios, adjusted for firm-level intangible capital, restore much of the predictive power that classical value models had lost. These findings support the broader thesis that understating intangible investment in financial reports leads to systematic valuation errors. This problem can be at least partially corrected through adjustments or capitalization.

Clausen and Hirth (2016) bring nuance to this discussion by examining the value relevance of different intangible categories. They find that externally visible intangibles, such as brand and customer relationships, are more consistently priced than internally developed intangibles, even though they are not consistently recorded in financial statements. This suggests that the market may partially adjust for intangibles but is more confident in those that can be externally verified.

Similarly, Barth and Clinch (1998), find slightly deviating results when considering revalued tangible assets into account. They compare the value relevance of tangible and intangible assets using data from the Australian market. Their results show that revalued tangible assets (e.g., property and equipment) have significant explanatory power for market value. However, the unrecorded portion of intangibles does not, a gap they attribute to poor accounting visibility. They argue that if intangible assets are not explicitly recognized and measured, they will not be consistently priced in capital markets.

2.5.2 Value Relevance of R&D Capitalization

The value relevance of research and development (R&D) has long been at the center of the debate surrounding the adequacy of financial reporting for innovation-driven firms. R&D is one of U.S. firms' largest and most strategically important intangible investments. However, its mandated immediate expense arguably leads to systematic underreporting of intangible capital and contributes to the market-to-book disconnect described in earlier sections.

Several studies propose and empirically test the capitalization of R&D expenditures as an alternative to immediate expense to address this disconnect. The logic is that R&D spending should be recognized as an asset and amortized over its useful economic life, similar to the treatment of tangible assets. This approach improves intertemporal matching of costs and benefits and increases the informativeness of book value and earnings.

Lev and Sougiannis (1996) provide a determining study on this topic. Using a sample of U.S. firms from 1975 to 1991, they estimate firm-specific capitalized R&D assets with an industry-specific amortization period. Their results show that both capitalized R&D and R&D-adjusted earnings are significantly associated with stock prices. Specifically, the coefficient of determination (R^2) improves by 25% when R&D capital is included in the valuation model. This strongly suggests that markets do price R&D as an economic asset, even when it is not reported in the financial statements.

Building on this, Aboody and Lev (1998) examine firms permitted to capitalize R&D under specific conditions, namely, software companies under SFAS 86, which allows capitalization after technological feasibility is established. Their findings confirm that capitalized software development costs are positively associated with market value, and that they contribute to better predictions of future earnings than expensed R&D alone. The case of software firms thus provides a quasi-natural experiment supporting the benefits of capitalization.

Lev (1999) further reinforces this view by demonstrating that the stock market reacts more strongly to R&D expenditures than to many other income statement components. He argues that investors adjust their valuation models to account for the economic significance of R&D, even when it is not recognized as an asset. However, this ability to “see through” accounting treatment has limits and leads to greater forecast dispersion and information asymmetry in high-R&D firms.

Sougiannis (1994) provides an earlier theoretical and empirical framework for treating R&D as an economic asset. He models R&D capitalization using amortization schedules and shows that adjusted book values have greater explanatory power for market capitalization. His work predates Lev and Sougiannis (1996) but aligns conceptually and methodologically, supporting the general thesis that capitalized R&D better reflects firm value.

King et al. (2024) contribute more recent evidence by distinguishing between acquired R&D, which is capitalized under GAAP as part of business combinations, and internally developed R&D, which remains expensed. Their results show that while capitalized intangibles are associated with value relevance, internally generated R&D is often undervalued, suggesting that current accounting standards result in inconsistent treatment of economically similar assets.

Another notable contribution comes from the study Boone and Raman (2001), who show that firms with higher unrecognized R&D capital experience lower liquidity and higher bid-ask spreads. This is attributed to the increased information risk investors face, who must estimate the unrecorded value of innovation activities. The findings imply that capitalization affects valuation accuracy and has implications for market efficiency.

Finally, Clausen and Hirth (2016) confirm that R&D exhibits the strongest market association among different intangible categories, particularly when capitalized using amortization-based estimates. They argue this is due to the relatively standardized and measurable nature of R&D investments compared to less tangible forms such as human or relational capital.

Together, these findings provide robust empirical support for the capitalization of R&D to partly restore the value relevance of financial statements. They also justify the core approach of this thesis, which adopts the Lev and Sougiannis (1996) methodology to estimate firm-level R&D capital and assess its relationship to market prices.

2.5.3 Empirical Motivation and Research Outlook

These findings confirm the critical gap in financial reporting. While capital markets appear to recognize the economic value of R&D, current accounting standards fail to represent this value systematically in financial statements. As Lev (1999) noted, the declining association between reported earnings and stock prices is particularly visible in intangible-intensive industries, suggesting that omitted R&D assets may contribute to the widening market-to-book ratio observed over recent decades.

This analysis contributes to this stream by examining the value relevance of capitalized R&D among U.S. firms reporting under U.S. GAAP. The empirical analysis focuses exclusively on firms subject to FASB standards, where R&D expenditures are generally expensed as incurred. This setting provides a consistent baseline for testing whether capitalizing and amortizing R&D improves the explanatory power of financial statement information with respect to share prices.

Specifically, the study adopts and updates the methodology developed by Lev and Sougiannis (1996), applying a perpetual inventory approach (Eisfeldt & Papanikolaou, 2013; Peters & Taylor, 2017) to construct firm-level capitalized R&D assets and adjusting earnings accordingly. Using a broad sample of U.S. firms covering fiscal years 1994 to 2023, the analysis follows their contemporaneous price model to assess whether R&D-adjusted earnings and book values offer additional value relevance to their unadjusted counterparts. Value relevance is defined as the degree to which accounting variables, such as earnings, book value, and R&D investment, are statistically associated with share prices, 3 months after fiscal year end. By extending the original framework by Lev and Sougiannis (1996) to more recent decades, this study not only revisits the pricing relevance of intangible investment but also assesses whether R&D capitalization helps explain part of the persistent divergence between market and book values in the modern knowledge economy.

3 Methodology

3.1 Data Sample

The empirical analysis is based on a panel of U.S. firms extracted from the merged COMPUSTAT/CRSP database, covering the fiscal years 1985 through 2023. While the final sample spans fiscal year-ends from 1994 to 2023, earlier data is required to construct amortized R&D assets. Specifically, historical R&D expenditures are needed to build up the firm-level capitalized R&D asset using a perpetual inventory method and industry-based amortization assumptions.

3.1.1 Data Extraction and Time Frame

The raw data was compiled by extracting all firm-year observations from the CRSP/COMPUSTAT merged database that include the variables necessary for valuation regressions: reported earnings (NI), R&D expense (XRD), sales (REVT), 4-digit SIC codes (SIC), and monthly stock prices (MTHPRC) with share counts (CSHPRI). These datapoints are linked using the CRSP/COMPUSTAT Merged Database identifiers.

3.1.2 Sample Construction

The raw data includes all firm-years with available financial and market data during the extraction period. Firm-year observations are not filtered at the point of download based on completeness of R&D data, as imputation strategies are used to estimate missing values and capitalized assets. This strategy ensures that firms with incomplete R&D reporting are not preliminarily excluded and allows maximum use of the available data when assigning amortization schedules and constructing R&D capital stocks. No filters are applied at the download stage beyond ensuring that relevant variables are present in the raw structure and double entries are avoided. Adjustments based on amortization feasibility, such as requiring a sufficient sequence of lagged R&D observations, are applied only after linking firm SIC codes to industry-specific amortization rates, as discussed in Section 3.2.3.

Values beyond the 1st and 99th percentiles are windsorized to account for misreporting and distortions. The resulting raw dataset contains 235,139 observations. Subsequent refinements to the analysis dataset are made at a variable level and, after that, at a regression level.

3.2 Variables and Measures

3.2.1 Scaled R&D

The foundation for constructing the capitalized R&D asset and adjustment variables lies in the firm's reported research and development expenditure (XRD), retrieved from COMPUSTAT. Since raw R&D levels are not directly comparable across firms of different sizes, the data is scaled by total sales:

$$XRD_{i,t}^{scaled} = \frac{XRD_{i,t}}{REVT_{i,t}}$$

This normalized variable serves as the target variable for imputation and instrumentation when firm-level XRD data are missing. Missing values in COMPUSTAT may reflect either non-reporting or zero actual investment but treating them as true zeroes can bias estimates and severely reduce the effective sample size. Therefore, a structured imputation method is applied to recover missing scaled R&D observations.

3.2.2 Industry-Based Imputation of Missing R&D

To recover as much information as possible on firm-level R&D and to avoid discarding observations with missing or unreported R&D expenses (XRD) this study tries a two-step "industry pooling" imputation approach that mirrors the methodology introduced by Lev and Sougiannis (1996). This approach assumes that peer firms operating in the same industry are exposed to similar technological environments and competitive R&D pressures, making industry-level behavior a credible proxy for firm-level behavior.

It is important to note that while Lev and Sougiannis (1996) use industry-level scaled R&D primarily to reduce firm-specific noise and smooth measurement error in the explanatory variable, the present study applies the same logic for a different purpose. Here, the industry instrument is used to impute missing R&D values at the firm level, thus providing a structured basis for filling in data gaps, rather than as a direct instrument in model estimation. This distinction underscores the role of the industry R&D variable not as a treatment for endogeneity in this context, but as a predictor in constructing a more complete dataset.

Step 1: Industry scaled R&D (Instrument). For each firm-year, an industry-level scaled R&D is computed using a leave-one-out methodology. Specifically, for firm i in year t, the industry instrument is calculated as:

$$XRD_{i,t}^{Industry} = \frac{\sum_{j \in S_{i,t},\, j \neq i} XRD_{j,t}}{\sum_{j \in S_{i,t},\, j \neq i} REVT_{j,t}}$$

where $S_{i,t}$ is the set of firms sharing the same four-digit SIC code as firm i in year t, $XRD_{j,t}$ is the R&D expense of any firm $j \neq i$ and $REVT_{j,t}$ are the sales generated by any firm $j \neq i$. To prevent small-sample distortions, the aggregation proceeds hierarchically: if the SIC4 group contains fewer than five firms, the calculation is repeated at the SIC3 level, and if necessary, further generalized to SIC2.

This procedure generates an "instrumental" scaled R&D that reflects the average behavior of a firm's closest industry peers, while excluding the firm itself to avoid mechanical correlation.

Step 2: Predictive Imputation via Cross-Sectional Regression. A strong positive relationship between firm-level scaled R&D and that of industry peers has been established in the literature (e.g., Lev & Sougiannis, (1996)). Exploiting this correlation, missing values for $XRD_{i,t}^{scaled}$ are imputed through predictive regressions. Specifically, for each calendar year and two-digit SIC group g, the following cross-sectional regression is estimated using firms with non-missing R&D data:

$$XRD_{i,t}^{scaled} = \alpha_{g,t} + \beta_{g,t} \cdot XRD_{i,t}^{Industry} + \varepsilon_{i,t}$$

For firms where no XRD values were available on COMPUSTAT, the fitted value from the above regression is used to assign an imputed scaled R&D:

$$\widehat{XRD_{i,t}^{scaled}} = \alpha_{g,t} + \beta_{g,t} \cdot XRD_{i,t}^{Industry}$$

This step ensures that firm-level estimates are sensitive to year-specific and industry-specific shifts in innovation behavior. To maintain reliability, this procedure is applied only to groups with at least five non-missing firm-level observations per year.

Step 3: Temporal Filling and Final Imputation. To avoid artificial gaps or volatility in R&D series, missing values not recovered through direct observation or regression prediction are filled using within-firm historical information. Specifically, the most recent non-missing value of $XRD_{i,t}^{scaled}$ for each firm is carried forward to the current year. This helps retain firms with intermittent reporting patterns. If neither a direct nor an imputed value is available, i.e., the firm has no usable R&D data across the entire window, the final fallback is to assign:

$$XRD_{i,t}^{scaled} = 0$$

This zero-filling rule follows Lev and Radhakrishnan (2005) and is used only when all other imputation efforts fail. While conservative, it allows the retention of otherwise usable financial data for firms where innovation activity is likely to be minimal or unreported.

The result is a filled-in series of firm-year R&D intensities that leverages peer information, regression prediction, and firm history to create a coherent and economically meaningful measure of R&D investment for downstream capitalization, earnings adjustment, and asset pricing analysis.

3.2.3 Amortization Rates and Data Requirements

To capitalize R&D expenditures into a stock of intangible assets, this study applies straight-line amortization rates that vary by industry, following the methodology used by Peters and Taylor (2017) and using amortization rate estimates provided by Li and Hall (2020), shown in Table 1. Based on updated data from the U.S. Bureau of Economic Analysis (BEA), these rates are derived using nonlinear least squares methods and reflect the expected decline in the economic value of R&D investments over time.

Table 1: Industry-specific Amortization Rates

Industry	δ
Computers and peripheral equipment	36.30%
Software	30.80%
Pharmaceuticals	11.20%
Semiconductor	22.60%
Aerospace product and parts	33.90%
Communication equipment	19.20%
Computer system design	48.90%
Motor vehicles, bodies and trailers, and parts	73.30%
Navigational, measuring, electromedical, and control instruments	32.90%
Scientific research and development	29.50%

Source: Lee and Hall (2020, Table 2)

This industry-specific approach builds upon earlier studies such as Lev and Sougiannis (1996) by accounting for sectoral differences in the longevity and realization of R&D benefits using more recent data. For instance, pharmaceuticals are assigned an amortization rate of 11.2%, implying a longer effective useful life for R&D (approximately 9 years). In comparison, motor vehicle and trailer manufacturers are assigned a 73.3% rate, reflecting more immediate R&D write-offs.

Each firm-year observation is matched to a four-digit SIC code and assigned an amortization rate δ_g using a manually constructed lookup table based on Li and Hall (2020) and Lev and Sougiannis (1996) (for mapping details, see Appendix 2). The resulting lookup table covers the most R&D-intensive industries identified by the BEA's R&D Satellite Account and updated for sectors that have gained importance in recent decades (e.g., software, semiconductors). The assignment prioritizes firm precision. Four-digit SIC codes are used wherever possible, without fallback aggregation. For firms whose SIC codes are not represented in the amortization table, a conservative fallback rate of 15% is applied, following Peters and Taylor (2017). The resulting depreciation rate δ_g is then used to construct the capitalized R&D asset (see Section 3.3.4).

Since R&D must be accumulated over several years to approximate its capitalized value, a sufficiently long time series of historical R&D data is required. This time horizon depends directly on the assigned amortization rate. For example, with the lowest rate in the sample

(11.2% for pharmaceuticals), at least nine years of lagged R&D data are needed to reach full capitalization:

$$Required\ History = \frac{100}{\delta_g}$$

To satisfy this requirement across all industry groups, the raw data extraction begins in fiscal year 1985, allowing for full amortization buildup starting with fiscal year 1994, the beginning of the main estimation window. After assigning amortization rates, firms are evaluated based on whether they have a continuous block of observation, including the newly generated $XRD_{i,t}^{scaled}$ that meets the required lookback horizon. If this continuity condition is not met, the firm is removed from the dataset for all affected specifications. After this adjustment, the updated raw dataset contains 167,305 firm-year observations. Eliminating observations before Fiscal Year 1994 results in a core sample containing 130,589 observations. However, this dataset is again adjusted for data availability based on the availability of individual regression variables to maximize the inclusion of valid data points.

3.2.4 Capitalized R&D and Amortization

To accurately incorporate R&D, this study capitalizes R&D expenditures into a capitalized R&D asset using a perpetual inventory method. This method treats R&D as an investment whose benefits depreciate over time, consistent with both theoretical models and empirical evidence in Lev and Sougiannis (1996) and Peters and Taylor (2017).

The R&D capital stock for each firm-year is constructed recursively, beginning from the earliest available R&D observation and applying straight-line amortization at the industry-specific rate δ_g. The R&D asset for firm i in year t, denoted $RDA_{i,t}$, is calculated as:

$$RDA_{i,t} = (1 - \delta_i) \cdot RDA_{i,t-1} + XRD_{i,t}$$

where:

- δ_g is the amortization rate assigned by SIC code,
- $RDA_{i,t-1}$ is the firm’s R&D asset from the previous year,
- $XRD_{i,t}$ is current-year R&D expense (or imputed R&D expense as discussed in Section 3.2.2).

This formula reflects that a fraction δ_g of the prior year's capital stock is amortized each year, while new R&D investment is added to the stock.

An annual amortization expense is also computed to calculate adjusted earnings that reflect capitalized R&D. This variable represents the economic depreciation of the firm's R&D stock in each period and is defined as:

$$RA_{i,t} = \delta_g \cdot RDA_{i,t-1}$$

The amortization variable $RA_{i,t}$ ensures that R&D expense recognition is spread across its expected useful life rather than being expensed entirely in the year incurred, as required under U.S. GAAP.

3.2.5 Earnings Measures

Following the framework introduced by Lev and Sougiannis (1996), the study includes both U.S. GAAP-based earnings and a reformulated measure that reflects capitalized R&D.

The baseline profitability measure is net income NI, reported under U.S. GAAP. This reflects total after-tax earnings and includes the immediate expensing of R&D, as standard accounting rules require.

For comparability across firms and consistency with price-based regressions, this variable is later scaled by shares outstanding during estimation to produce a per-share measure.

To evaluate the value relevance of R&D capitalization, a second measure of earnings is constructed by adjusting net income to reflect a capital treatment of R&D. Specifically, R&D expense is added back, and only the amortization portion is subtracted:

$$NI_{i,t}^{adj} = NI_{i,t} + XRD_{i,t} - RA_{i,t}$$

Where:

- $XRD_{i,t}$ is reported or imputed R&D expense,
- $RA_{i,t}$ is the R&D amortization charge.

This adjusted earnings figure represents net income under an alternative accounting treatment that capitalizes R&D. Like the reported version, this variable is also scaled by shares outstanding at the regression stage.

3.2.6 Dependent Variable: Stock Price

The dependent variable in all main regression models is the firm's stock price observed three months after the end of its fiscal year. This timing, standard in the literature (e.g., Lev & Sougiannis, 1996; Aboody & Lev, (1998)), allows sufficient time for audited annual financial statements to be released and incorporated into market valuations.

$$P_{i,t} = Monthly\ closing\ price\ in\ CRSP, three\ months\ after\ fiscal\ year\ end$$

This forward-looking price is assumed to reflect all publicly available financial information about the fiscal year t, and it is matched precisely using the CRSP calendar-month end data.

3.3 Model Specification

This thesis employs a cross-sectional value relevance framework to evaluate whether capitalizing R&D improves the association between accounting information and firm valuation. All models are estimated using ordinary least squares (OLS) with Huber–White robust standard errors to correct for heteroskedasticity. Two versions of each regression are run:

- One using the imputed sample, which includes imputed R&D variables where needed
- One using the reported-only sample, limited to observations with R&D available from COMPUSTAT

3.3.1 Core Price Regressions

All variables are expressed in per-share terms, i.e., reported earnings ($NI_{i,t}$), adjusted earnings ($NI_{t,i}^{adj}$), and the capitalized R&D asset ($RDA_{i,t}$) scaled by the number of diluted shares outstanding to ensure comparability with the stock price three months after fiscal year end $P_{i,t}$.

Model 1: Parsimonious Price Model

$$P_{i,t} = \alpha + \beta_1 \cdot NI_{i,t} + \beta_2 \cdot \left(NI_{t,i}^{adj} - NI_{i,t}\right) + \varepsilon_{i,t}$$

This model tests whether the distortion caused by expensing R&D $\left(NI_{t,i}^{adj} - NI_{i,t}\right)$ strengthens the value relevance of reported earnings. A significant and positive β_2 would indicate that markets recognize the understatement in GAAP earnings and value the "recovered" R&D-adjusted income accordingly.

Model 2: Parsimonious Price Model with Capitalized R&D Asset

$$P_{i,t} = \alpha + \beta_1 \cdot NI_{i,t} + \beta_2 \cdot \left(NI_{t,i}^{adj} - NI_{i,t}\right) + \beta_3 \cdot RDA_{i,t} + \varepsilon_{i,t}$$

This model extends the prior specification by including the R&D capital stock ($RDA_{i,t}$) as a stand-alone explanatory variable. The aim is to test whether markets value R&D directly as an economic asset, separate from its income effects. A positive and significant result would indicate that the capital market prices in the unrecognized portion of firm assets are created by R&D investment. An increase in explanatory power over Model 1 would provide empirical support for capitalizing R&D in valuation models.

Together, these two regressions provide a comprehensive framework for evaluating the value relevance of R&D as an intangible investment remaining unrecognized in financial reporting. By separating the income effects of R&D from its capitalized asset value, the models assess whether and how investors incorporate unrecognized intangible assets into equity pricing. This dual structure allows the analysis to go beyond conventional accounting metrics and examine whether the capitalization of R&D improves the financial statement's ability to reflect the economic reality of firms. In doing so, the models directly address whether capital markets compensate for the reporting limitations imposed on internally developed intangibles.

3.3.2 Annual Cross-Section Estimation

Each specification is estimated annually, producing a time series of coefficients for the 1994–2023 sample period. This design follows Lev and Sougiannis (1996) and allows an analysis of average coefficient magnitudes and their stability over time.

The mean coefficient for each variable is calculated as:

$$\overline{\beta_k} = \frac{1}{T}\sum_{t=1}^{T} \beta_{k,t}$$

Corresponding t-statistics are computed using a one-sample t-test on the series of yearly coefficient estimates. This approach formally tests the null hypothesis $H_0 : \beta_{k,t} = 0$ and derives the t-statistic as the ratio of the mean to its standard error, based on the time-series distribution of the yearly coefficients.

It enables an analysis of the coefficients' temporal consistency and helps to detect structural shifts in value relevance across different market environments. In particular, it allows for assessing whether the explanatory power of capitalized R&D holds across years or is limited to specific periods.

3.4 Summary Statistics

3.4.1 Estimation Samples and Data Filtering

All final estimations are based on filtered versions of the raw dataset, winsorized at the 1st and 99th percentiles, to ensure comparability across regression specifications and eliminate distortions caused by extreme values and inconsistent information. The original data extract from CRSP/COMPUSTAT includes 130,589 firm-year observations from fiscal years 1994 to 2023.

Two distinct estimation samples are constructed from this base:

- An **imputed sample**, which incorporates firm-year observations with either reported or imputed R&D.
- A **reported-only sample** includes observations where R&D expenditure is directly available from COMPUSTAT and all downstream capitalized components are derived without imputation.

The analysis requires clean and consistent input data for key regression variables related to earnings, R&D, and market valuation. A structured data filtering and trimming process was applied separately to each dataset to meet these conditions.

First, observations were removed if they were missing any of the key regression variables. Specifically, an observation had to contain non-missing values for the three-month-ahead stock price $P_{i,t}$, reported earnings $NI_{i,t}$, R&D-adjusted earnings $NI_{t,i}^{adj}$, and capitalized R&D asset $RDA_{i,t}$.

Following this, each dataset was further cleaned by trimming extreme values. Observations were trimmed at the 1st and 99th percentiles for each regression variable to limit the influence of outliers. This step was critical given the highly skewed distribution of certain variables, which can otherwise dominate OLS estimation and inflate standard errors. These two filtering procedures were applied separately to the two distinct estimation samples used in this thesis.

3.4.2 Imputed Sample

The full data set includes all firm-year observations for which at least one R&D-related variable is either directly reported or could be imputed. After applying the missing-variable filter and winsorizing at the 1^{st} and 99^{th} percentiles, the imputed sample consists of 73,340 firm-year observations and a total of 7,896 firms. The corresponding summary statistics are shown in Table 2.

Table 2: Descriptive Statistics – Imputed sample

Variable	Mean	Median	Std. Dev.	Skewness	Kurtosis	Min	Max
$P_{i,t}$	23.60	14.74	25.96	1.98	4.66	0.22	159.52
$NI_{i,t}$	0.77	0.54	2.81	-5.72	575.25	-203.59	131.54
$NI_{t,i}^{adj}$	16.31	0.62	1073.82	62.25	7401.70	-60224	134697
$NI_{t,i}^{adj} - NI_{i,t}$	15.53	0.02	1073.81	62.26	7402.08	-60221	134697
$RDA_{i,t}$	-104.25	1.76	5463.54	-96.60	10860	-763280	14317

Underlying variables include net income ($NI_{i,t}$), adjusted net income ($NI_{t,i}^{adj}$), and the capitalized R&D asset ($RDA_{i,t}$), scaled by shares outstanding. Values beyond the 1^{st} and 99^{th} percentiles are removed. N = 73,340.

Reported net income ($NI_{i,t}$) across firms in this sample is relatively stable, with most firms showing moderate earnings or manageable losses. In contrast, the adjusted earnings ($NI_{t,i}^{adj}$), which incorporates capitalized R&D and amortization, exhibits far greater variation. While the median firm shows only a modest adjustment from capitalization, the full distribution is heavily skewed by firms with extreme R&D levels or low share counts. Values range from -60,224 to over 134,000 dollars per share, despite accounting for extreme values. These outliers highlight the mechanical volatility introduced by capitalizing imputed R&D and scaling by shares.

Although the median capitalized R&D asset value ($RDA_{i,t}$), remains positive, the average is pulled negative by a small number of extreme downward values, exhibiting both a minimum below –760,000 and a maximum over 14,300 dollars per share. These values underscore the compounding effect of the three-step process: imputing missing R&D, accumulating it via amortization, and finally scaling it by firm-specific share counts.

The extreme dispersion observed in both adjusted earnings and R&D asset values originates from the structure of the imputation procedure. Because missing R&D values are estimated using peer-based industry averages, firms operating in heterogeneous industries or with atypical R&D-to-sales ratios relative to their sector may receive imputed values that substantially over- or understate their true economic investment. Once these values are accumulated and amortized into multi-period R&D capital stocks, the resulting asset values can diverge significantly across firms. When scaled by shares outstanding, these differences are further exaggerated, resulting in the severe skewness and kurtosis shown in the distributions.

In contrast, stock prices three months after fiscal year-end are $P_{i,t}$ are much more conventionally distributed. With a median value of 14.74 and a mean of 23.60, the dependent variable used in price regressions is relatively stable, providing a reliable benchmark for assessing the informativeness of adjusted earnings and intangible assets.

While this imputed sample maximizes coverage and preserves firm-years with partially missing R&D data, it introduces considerable volatility into the explanatory variables. For this reason, and to ensure the reliability of data interpretation, the subsequent analysis focuses on the reported-only dataset, which contains only observations with directly disclosed R&D expenditures. This cleaner sample serves as the main base throughout the empirical sections of this study, providing greater consistency and minimizing distortions caused by imputation.

3.4.3 Reported-only Sample

The second estimation sample consists exclusively of firm-year observations for which R&D data were directly reported in COMPUSTAT, requiring no imputation. While this comes at the cost of reduced coverage, it provides a more reliable benchmark than including imputed data based on industry peers.

After applying the same filtering, removing observations with missing regression variables, and trimming at the 1st and 99th percentiles, the final reported-only sample consists of 44,309 firm-year observations and 5,166 firms. This results in the summary statistics shown in Table 3.

Table 3: Descriptive Statistics – Reported-only Sample

Variable	Mean	Median	Std. Dev.	Skewness	Kurtosis	Min	Max
$P_{i,t}$	21.72	13.63	22.85	1.70	3.03	0.45	127.90
$NI_{i,t}$	0.66	0.43	1.53	0.49	1.44	-4.57	6.60
$NI_{t,i}^{adj}$	0.77	0.54	1.58	0.51	1.40	-5.95	8.26
$NI_{t,i}^{adj} - NI_{i,t}$	2.14	1.29	2.53	1.84	3.69	0.00	14.38
$RDA_{i,t}$	21.72	13.63	22.85	1.70	3.03	0.45	127.90

Underlying variables include net income ($NI_{i,t}$), adjusted net income ($NI_{t,i}^{adj}$), and the capitalized R&D asset ($RDA_{i,t}$), scaled by shares outstanding. All variables are winsorized at the 1st and 99th percentiles. N = 44,309.

The variables in this sample show considerably more stable behavior. Reported earnings ($NI_{i,t}$) are modest and symmetrically distributed, with a mean of 0.66 and a median of 0.43. The adjusted earnings ($NI_{t,i}^{adj}$) are similar in scale, with a mean of 0.77 and a median of 0.54.

The capitalized R&D asset ($RDA_{i,t}$) indicates a median value of 13.63 and a mean of 21.72, suggesting relatively consistent R&D investment across firms with direct reporting. The distribution of this variable shows moderate skewness and kurtosis, with a maximum value of 127.90 and a minimum of 0.45.

Stock prices three months after fiscal year-end ($P_{i,t}$) are similarly well-behaved in this sample, with a mean of 21.72 and a median of 13.63. Overall, this dataset presents a cleaner empirical environment in which to evaluate the capital market relevance of reported R&D investments, without the added complexity or potential biases introduced by a reconstruction of missing values.

The relatively narrow ranges, low skewness, and limited dispersion in all key variables suggest that this sample's observed earnings and R&D adjustments are more stable. In contrast to the imputed dataset, where estimation noise, industry-level heterogeneity, and compounding effects led to extreme values, the reported-only sample offers greater confidence in the integrity of the underlying financial data.

3.4.4 Correlation Analysis

To further understand the relationships among key regression variables, pairwise Pearson correlation matrices were computed for both the imputed and reported-only samples. This analysis provides insight into the data's internal consistency and helps assess whether imputation affects the structural relationships between variables.

Table 4. Correlation Matrix – Imputed sample

Variable	$P_{i,t}$	$NI_{i,t}$	$NI_{t,i}^{adj}$	$NI_{t,i}^{adj} - NI_{i,t}$	$RDA_{i,t}$
$P_{i,t}$	1				
$NI_{i,t}$	0.4643	1			
$NI_{t,i}^{adj}$	-0.0059	0.0051	1		
$NI_{t,i}^{adj} - NI_{i,t}$	-0.0071	0.0025	0.9999	1	
$RDA_{i,t}$	0.0084	0.0045	-0.8506	-0.8506	1

Variables are scaled per share. N = 73,340

Table 5. Correlation Matrix – Reported-only Sample

Variable	$P_{i,t}$	$NI_{i,t}$	$NI_{t,i}^{adj}$	$NI_{t,i}^{adj} - NI_{i,t}$	$RDA_{i,t}$
$P_{i,t}$	1				
$NI_{i,t}$	0.6422	1			
$NI_{t,i}^{adj}$	0.6677	0.9736	1		
$NI_{t,i}^{adj} - NI_{i,t}$	0.2154	0.0458	0.2725	1	
$RDA_{i,t}$	0.2363	0.0790	0.1333	0.2504	1

Variables are scaled per share. N = 44,309

The correlation patterns underscore the differing quality and behavior of the two datasets. In the reported-only sample shown in Table 5, variable relationships are statistically meaningful. Stock prices ($P_{i,t}$) are similarly correlated with both reported earnings ($NI_{i,t}$, 0.64) and adjusted earnings ($NI_{t,i}^{adj}$, 0.67), and show a moderate positive association with the capitalized R&D asset ($RDA_{i,t}$, 0.24). Notably, the correlation between $NI_{i,t}$, and $NI_{t,i}^{adj}$ is 0.97, reflecting the relatively small but consistent adjustment introduced by capitalizing and amortizing R&D. These values suggest that markets respond to both recorded and unrecorded components of firm performance when such components are based on disclosed information.

By contrast, the imputed sample indicated in Table 4 reveals much weaker internal coherence. The correlation between $NI_{t,i}^{adj}$ and $P_{i,t}$ becomes negative (–0.006), and its near-perfect correlation with the earnings misstatement ($NI_{t,i}^{adj} - NI_{i,t}$, 0.9999) highlights their mechanical dependency rather than any informational distinction. Similarly, the capitalized R&D Asset ($RDA_{i,t}$) exhibits a strong negative correlation with both adjusted earnings ($NI_{t,i}^{adj}$,-0.85) and the earnings misstatement ($NI_{t,i}^{adj} - NI_{i,t}$, -0.85) yet remains essentially uncorrelated with the share price ($P_{i,t}$, 0.008). These patterns directly confirm the distortions introduced by the imputation process, as previously discussed in the descriptive statistics section.

In line with the descriptive statistics, these results suggest that the imputed values introduce estimation noise or structural inconsistencies that disrupt the empirical relationship between firm fundamentals and their market value. One can infer that, while imputation extends the dataset size, it may dilute the economic signal of R&D capitalization. The reported-only sample, in contrast, provides cleaner and more interpretable relationships between variables, reinforcing its role as the more reliable basis for the regression analysis.

4 Empirical Results

This chapter presents the results of the price regressions based on the methodological framework outlined in Chapter 3. Both pooled ordinary least squares (OLS) regressions and annual cross-sectional regressions are estimated to assess the value relevance of reported earnings, adjusted earnings, and capitalized R&D assets. Results are reported for the reported-only sample, which is referred to as the main sample of this study. Emphasis is placed on the cross-sectional analysis and its development over time, given its central role in evaluating the persistence and consistency of value relevance across accounting treatments.

4.1 Pooled OLS Regression Results

The following sections present the results of the pooled (OLS) regressions (Table 6). In pooled OLS regressions, all firm-year observations are treated as a single combined cross-section, without accounting for firm identity or year-specific effects. This approach estimates the average relationship between variables across the sample, but it does not control for time trends or unobserved heterogeneity at the firm level. It is used here primarily to establish a benchmark for explanatory power and coefficient stability, before transitioning to the year-by-year cross-sectional analysis presented in Chapter 4.2.

Table 6: Pooled-OLS

Dependent Variable		Independent Variables					
		Intercept	$NI_{i,t}$	$NI_{t,i}^{adj} - NI_{i,t}$	$RDA_{i,t}$	$adj.R^2$	**N**
1.	$P_{i,t}$	14.179	9.486*** (120.16)	11.766*** (38.12)	-	0.45	44,309
2.	$P_{i,t}$	11.657	9.335*** (120.17)	9.429*** (33.25)	1.350*** (35.64)	0.47	44,309

*T-statistics are reported in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10. All variables are scaled per share. Estimates are based on pooled OLS regressions with robust standard errors.*

In Model 1, both $NI_{i,t}$ and $NI_{t,i}^{adj} - NI_{i,t}$ are strongly positively associated with stock price $P_{i,t}$, indicating statistical significance and confirming the expected value relevance of earnings information. The adjusted R^2 reaches 0.45, showing that the earnings variables alone explain nearly half of the variation in stock price. The coefficient on $NI_{i,t}$ is 9.486 (t = 120.16), while $NI_{t,i}^{adj} - NI_{i,t}$ has a larger coefficient of 11.766 (t = 38.12).

Considering the variables' respective means, 0.66 for $NI_{i,t}$ and 2.14 for $NI_{t,i}^{adj} - NI_{i,t}$ (Table 3), the average economic contribution is approximately 6.261 for reported earnings and a much larger 25.179 for the earnings' misstatement. This suggests that while both variables matter, investors place substantially greater economic weight on the portion of earnings that would have been capitalized if R&D were treated as an asset. This aligns with a key theme of this study: R&D investment typically enhances future earnings and cash flows. The strong t-statistics further reinforce that both effects are precisely estimated and meaningful, strengthening the case for treating R&D as an asset rather than a period expense.

When adding the capitalized R&D asset $RDA_{i,t}$ in Model 2, the explanatory power improves to 0.47. The coefficient on $RDA_{i,t}$ is 1.350 (t = 35.64), statistically and economically significant. Given its large mean of 21.72, the average contribution of $RDA_{i,t}$ to the stock price is approximately 29.32, greater than either of the other two components. This confirms that markets do indeed treat internally developed R&D as a valuable off-balance-sheet economic asset.

Additionally, the inclusion of $RDA_{i,t}$ slightly reduces the magnitude of the coefficients on $NI_{i,t}$ (9.335) and $NI_{t,i}^{adj} - NI_{i,t}$ (9.429), but both remain statistically significant, supporting the idea that all three variables offer incremental explanatory power.

The consistently high t-statistics in this sample, ranging from 35.64 to 120.17, reflect both the large number of observations and the quality of the included variables. This is consistent with the correlations shown in Table 5. Despite a high correlation between $NI_{t,i}^{adj}$ and $NI_{i,t}$ (ρ = 0.97), the earnings' misstatement $NI_{t,i}^{adj} - NI_{i,t}$ retains sufficient variation relative to $NI_{i,t}$, which avoids multicollinearity and allows for the contribution of explanatory power to the regression. Similarly, the moderate correlation between $RDA_{i,t}$ and the other predictors (ρ = 0.13–0.25) does not result in any multicollinearity problems, allowing for more stable and interpretable estimates.

These results validate the core hypothesis of this study, which is that capitalizing R&D restores the value relevance of financial statements and aligns reported accounting figures more closely with market perceptions. They also justify the emphasis placed on the reported-only sample in the remainder of the analysis.

The results for the pooled OLS regression on the imputed sample are shown in Appendix 2.

4.2 Annual Cross-Sectional OLS Results

The following section presents the results of annual cross-sectional regressions, run separately for each fiscal year from 1994 to 2023. In contrast to the pooled OLS regressions in Section 4.1, where all firm-year observations were treated as a single combined sample, this approach estimates regression coefficients independently for each year, yielding a time series of coefficient estimates. These yearly results are then aggregated by computing time-series averages, providing summary measures over the entire 30-year sample period. Each year's regression is given equal weight in this aggregation, regardless of its sample size.

As described in Section 3.3.2, this setup follows the methodology of Lev and Sougiannis (1996) and enables an analysis of the temporal consistency of the price-earnings relationship and the persistence of R&D's value relevance over time.

4.2.1 Mean Coefficients (1994-2023)

Table 7 presents the results from the annual cross-sectional regressions. For both model specifications, the reported values reflect the average coefficients and associated t-statistics computed across 30 yearly regressions covering the period from 1994 to 2023.

Table 7: Annual Cross-Sectional OLS

		Independent Variables					
Dependent Variable		**Intercept**	$NI_{i,t}$	$NI_{t,i}^{adj} - NI_{i,t}$	$RDA_{i,t}$	$adj.R^2$	**N**
1.	$P_{i,t}$	14.480	9.406***	13.248***	-	0.48	44,309
			(27.889)	(10.606)			
2.	$P_{i,t}$	12.103	9.274***	10.913***	1.260***	0.51	44,309
			(26.940)	(10.674)	(14.850)		

*T-statistics are reported in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10. All variables are scaled per share. Estimates are based on annual cross-sectional regressions; reported coefficients are time-series means.*

As expected, the mean coefficients signal strong valuation relationships. Model 1 shows an adjusted R^2 of 0.48, suggesting that nearly half of the variation in the dependent variable is explained by the model. Both coefficients are highly statistically significant, with $NI_{i,t}$ estimated at 9.406 (t = 27.889) and $NI_{t,i}^{adj} - NI_{i,t}$ at 13.248 (t = 10.606).

Importantly, the mean of $NI_{i,t}$ is 0.66, whereas the mean of $NI_{t,i}^{adj} - NI_{i,t}$ is substantially higher at 2.14 (Table 5). This implies that both the coefficient and the magnitude of the adjustment term are significant, making its average impact on the dependent variable even greater than that of reported earnings.

These results suggest that investors place considerable weight on R&D-related earnings adjustments, reinforcing the view that capitalizing R&D investments may provide more decision-relevant information than expensing them.

Incorporating the capitalized R&D asset $RDA_{i,t}$ in Model 2 increases the explanatory power slightly, with an adjusted R^2 of 0.51. The coefficient on the capitalized R&D variable is 1.26 (t = 35.17), which is both economically and statistically significant, given its relatively large mean value of 21.72 (Table 5). On average, this implies a contribution of approximately 27.37 to the dependent variable from the R&D asset alone.

Including this variable leads to a modest reduction in the coefficient magnitudes of both $NI_{i,t}$ (9.274) and $NI_{t,i}^{adj} - NI_{i,t}$, (10.913) but all remain significant. The mean values of these variables remain at 0.66 and 2.14 (Table 5), respectively, implying continued but comparatively minor average contributions of roughly 6.12 and 23.35, respectively.

This result confirms the study's core hypothesis that both net investment into R&D and capitalized R&D convey incremental value-relevant information. Investors appear to treat R&D assets as unrecognized but economically meaningful capital.

The respective analyses on the imputed sample are attached to Appendix 3.

4.2.2 Time Variation in Value Relevance

Model 1 is again estimated over six consecutive five-year intervals. Table 8 presents the resulting coefficient means and associated t-statistics, alongside adjusted R^2 values and sample sizes for each subperiod.

Table 8: 5y Average Annual Cross-Sectional OLS – Reported-only Sample: Model 1

	Model 1					
	Independent Variables					
Dependent Variable	**Intercept**	$NI_{i,t}$	$NI_{t,i}^{adj} - NI_{i,t}$	$RDA_{i,t}$	$adj.R^2$	**N**
$P_{i,t}$ *1994 – 1998*	10.847	8.601*** (25.602)	8.331*** (11.179)	-	0.496	7,762
$P_{i,t}$ *1999 – 2003*	13.026	7.057*** (14.303)	10.838*** (7.554)	-	0.388	8,417
$P_{i,t}$ *2004 – 2008*	11.531	9.324*** (9.000)	8.738*** (11.699)	-	0.554	8,805
$P_{i,t}$ *2009 – 2013*	13.950	10.345*** (20.897)	8.911*** (8.110)	-	0.538	7,566
$P_{i,t}$ *2014 – 2018*	17.952	11.654*** (45.947)	17.213*** (10.989)	-	0.509	6,529
$P_{i,t}$ *2019 – 2023*	19.575	9.454*** (22.199)	25.455*** (15.877)	-	0.418	5,230

*T-statistics are reported in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10. All variables are scaled per share. Estimates are based on annual cross-sectional regressions; reported coefficients are time-series means.*

Across all intervals, both reported earnings $NI_{i,t}$ and the earnings' misstatement $NI_{t,i}^{adj} - NI_{i,t}$ display consistently positive and highly significant coefficients. The coefficient on $NI_{i,t}$ ranges from 7.057 in the early 2000s to 11.654 in the 2014–2018 period, with t-statistics consistently above 9.000. This reflects the ongoing unit relevance of earnings for valuation, albeit with moderate variation across time.

$NI_{t,i}^{adj} - NI_{i,t}$ also remains robustly positive and statistically significant across all time windows. Its magnitude rises substantially in later periods, from 8.331 in the late 1990s to 25.455 in the 2019–2023 window. This trend may reflect the growing importance of R&D-related earnings distortion as intangible investment becomes more central to firm value. The corresponding t-statistics further emphasize this pattern, with robust signal strength in the final subperiod (t = 15.877).

Adjusted R^2 values range from 0.388 to 0.554 across subperiods, with no clear directional trend. This implies that while model fit varies with market conditions and sample composition, the combined explanatory power of earnings and their R&D adjustment remains materially strong throughout the period.

The results of the five-year segmented annual regressions for Model 2 are presented in Table 9. The inclusion of the capitalized R&D asset ($RDA_{i,t}$) alongside earnings variables leads to consistently strong explanatory power, with improved adjusted R^2 values ranging from 0.420 to 0.566.

Table 9: 5y Average Annual Cross-Sectional OLS – Model 2

	Model 2					
	Independent Variables					
Dependent Variable	**Intercept**	$NI_{i,t}$	$NI^{adj}_{t,i} - NI_{i,t}$	$RDA_{i,t}$	$adj.R^2$	**N**
$P_{i,t}$ *1994 – 1998*	8.659	8.156*** (26.041)	6.218*** (11.348)	1.351*** (17.338)	0.529	7,762
$P_{i,t}$ *1999 – 2003*	10.516	7.017*** (12.368)	9.291*** (7.317)	1.379*** (12.443)	0.420	8,417
$P_{i,t}$ *2004 – 2008*	10.024	9.293*** (8.910)	7.097*** (9.069)	0.870*** (11.076)	0.566	8,805
$P_{i,t}$ *2009 – 2013*	12.537	10.256*** (20.859)	7.934*** (8.634)	0.703*** (3.133)	0.549	7,566
$P_{i,t}$ *2014 – 2018*	14.587	11.556*** (44.975)	14.207*** (11.337)	1.583*** (9.095)	0.531	6,529
$P_{i,t}$ *2019 – 2023*	16.296	9.366** (20.516)	20.732*** (15.800)	1.672*** (12.346)	0.440	5,230

*T-statistics are reported in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10. All variables are scaled per share. Estimates are based on annual cross-sectional regressions; reported coefficients are time-series means.*

$NI_{i,t}$ remains highly significant throughout all subperiods. The mean coefficient estimates range from 7.017 (1999–2003) to 11.556 (2014–2018), with t-statistics consistently above the thresholds. The stability and magnitude of these coefficients once again underline the dominant role of earnings in market valuation, even when adjusting for unrecognized R&D.

$RDA_{i,t}$ is statistically significant in every subperiod, with coefficients ranging from 0.703 to 1.672. Its significance and effect size suggest that the market recognizes R&D as a value-relevant asset. This reinforces the argument that uncapitalized R&D materially distorts firms' perceived value and can be meaningfully corrected when reliable inputs are available.

$NI^{adj}_{t,i} - NI_{i,t}$ is also statistically significant in all periods. With coefficients increasing over time, from 6.218 in the earliest subperiod to 20.732 in 2019–2023, the coefficient indicates that the marginal valuation relevance of the earnings misstatement has grown over time. Additionally, this trend aligns with the earlier Model 1 results and reflects a growing divergence between reported and adjusted earnings, potentially due to the increasing importance of intangible investments that are not adequately reflected in U.S. GAAP. The size and significance of $NI_{t,i}^{adj} - NI_{i,t}$ suggest that market participants recognize and respond to these distortions.

The results for an equivalent analysis on the imputed dataset can be found in Appendices 4 and 5.

Due to its consistent meaningfulness and significant contributions, the results allow for an analysis on a yearly basis (Figures 1 and 2). The tables for Model 1 and Model 2 are shown in Appendix 6 and Appendix 7, respectively.

Figure 1: Yearly Annual Cross-Sectional OLS – Model 1 (1994–2023)

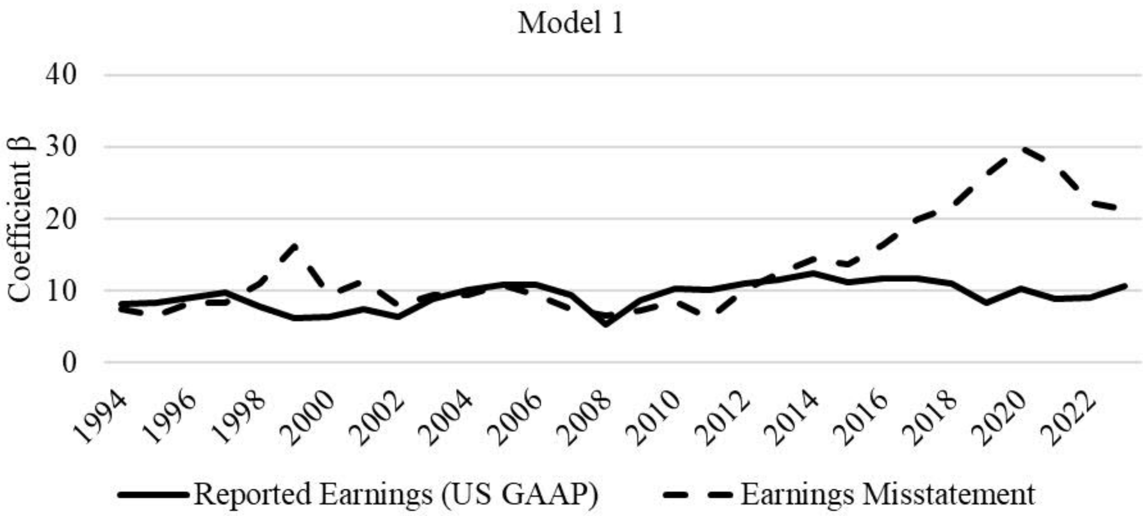
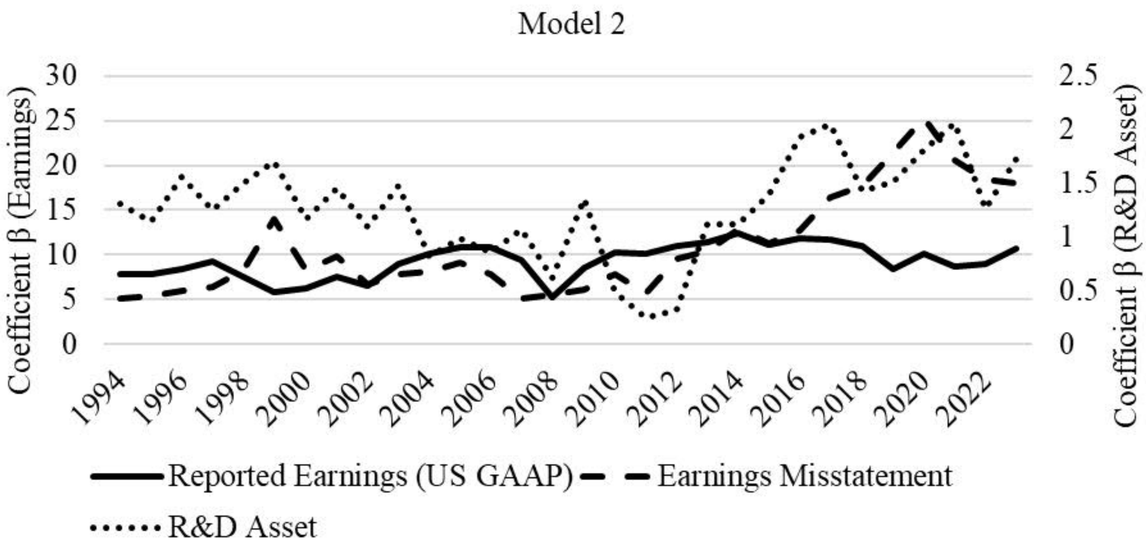


Figure 2: Yearly Annual Cross-Sectional OLS – Model 2 (1994–2023)



In the early years (1994–2003), $NI_{i,t}$ and $NI_{t,i}^{adj} - NI_{i,t}$ were significant in both models. While similar in magnitude for both variables, there was no significant variation in the effects. However, both models saw a local peak in 1999 with $NI_{t,i}^{adj} - NI_{i,t}$ indicating a significant coefficient of 16.130 in Model 1 and 13.926 in Model 2 and $NI_{i,t}$ remaining at 6.186 and 5.852, respectively. Starting around 2004 and coinciding with the start of the digitalization wave and the rise of platform business models, the role of R&D began to intensify slowly. In 2008, however, all coefficients recognize a significant drop, most likely due to effects related to the financial crisis. From 2013 onward, and especially in the period 2016–2023, the coefficient on $NI_{t,i}^{adj} - NI_{i,t}$ in Model 1 increasingly exceeded that of $NI_{i,t}$. For example, in 2020, the $NI_{t,i}^{adj} - NI_{i,t}$ coefficient reached 29.96 versus just 10.26 for $NI_{i,t}$. This reversal suggests that the expensed portion of R&D, when capitalized, became a more important predictor of market value than earnings alone, a pattern that persisted throughout the COVID-19 period.

Model 2 mirrors this trend, showing steady and statistically significant contributions of $RDA_{i,t}$ from 2010 onward. Its coefficients ranged from 0.243 in 2011 to over 2.048 by 2017 and 2.057 in 2021, mirroring growing investor reliance on off-balance-sheet intangible signals. Furthermore, explanatory power (adj. R^2 remains in the 0.50–0.60 range) persisted even as the role of traditional earnings decreased.

4.3 R&D Intensity Subsample Analysis

As a robustness check, this study also investigates whether the value relevance of capitalized R&D is particularly prominent among firms with high R&D intensity. Building on Lev and Sougiannis (1996), who find stronger effects in such firms, a supplementary analysis isolates the upper quartile of the sample based on R&D capital relative to total assets. This serves to validate the core results in a subsample where intangible investment is expected to be a more dominant driver of firm valuation.

4.3.1 Summary Statistics

Table 10 presents a comparison of the distribution of the R&D capital to total asset ratio ($\boldsymbol{RDA_{i,t} / TA_{i,t}}$) between the main sample (reported-only sample) and its upper quartile. This ratio serves as a proxy for intangible asset intensity, indicating the proportion of a firm’s asset base derived from accumulated R&D investments.

Table 10: Descriptive Statistics – R&D Intensity

Variable	Mean	Median	Std. Dev.	Skewness	Kurtosis	Min	Max
Reported-only Sample							
$\boldsymbol{RDA_{i,t} / TA_{i,t}}$	0.36	0.12	1.17	24.65	1197.16	0.00	90.19
Upper Quartile							
$\boldsymbol{RDA_{i,t} / TA_{i,t}}$	1.15	0.62	2.15	14.79	397.25	0.33	90.19

Reported-only Sample: N = 73,340; Upper Quartile: N = 11,78

In the main sample, the mean R&D capital to total assets ratio is 0.36, with a median of 0.12. This suggests that while most firms allocate a relatively small share of their asset base to capitalized R&D, some exhibit substantially higher intensities. The distribution is heavily right-skewed (skewness = 24.65) and exhibits extreme kurtosis (1,197.16), indicating the presence of a few firms with exceptionally high R&D-to-asset ratios that stretch the tail of the distribution.

By contrast, firms in the upper quartile report a mean R&D capital to total assets ratio of 1.15 and a median of 0.62. The standard deviation (2.15) and skewness (14.79) remain high, and the kurtosis, while lower at 397.25, still indicates a highly peaked distribution with heavy tails. This reflects the fact that even within the top quartile, a small number of firms maintain extremely large R&D asset proportions.

This comparison confirms that the upper quartile captures a distinct set of firms whose valuation is more likely to be influenced by R&D-related assets, justifying their use as a focused subsample for robustness analysis in the following regression sections.

4.3.2 Value Relevance Regressions – Upper Quartile

Table 11 presents the results of the annual cross-sectional regressions estimated on the upper quartile of firms by R&D intensity. Model 1 includes reported earnings and the earnings misstatement term, while Model 2 adds the capitalized R&D asset.

Table 11. Annual Cross-Sectional OLS – R&D Intensity upper Quartile

		Independent Variables					
Dependent Variable		**Intercept**	$NI_{i,t}$	$NI_{t,i}^{adj} - NI_{i,t}$	$RDA_{i,t}$	$adj.R^2$	**N**
1.	$P_{i,t}$	10.669	6.138*** (23.097)	11.685*** (12.489)	-	0.36	11,078
2.	$P_{i,t}$	4.033	5.490*** (25.572)	10.190*** (14.019)	1.863*** (26.732)	0.50	11,078

*T-statistics are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All variables are scaled per share. Estimates are based on annual cross-sectional regressions; reported coefficients are time-series means.*

The upper quartile subsample exhibits strong coefficients on the R&D-related variables, but the differences from the main sample are more moderate than anticipated. In Model 1, the coefficient on the earnings misstatement $NI_{t,i}^{adj} - NI_{i,t}$ is 11.685, nearly matching the baseline estimate of 13.248, while the coefficient on reported earnings $NI_{i,t}$ drops from 9.406 to 6.138. Both coefficients indicate a slight decrease in the marginal impact on the share price. The adjusted R^2 declines from 0.48 to 0.36, suggesting that in R&D-intensive firms, reported earnings and adjusted earnings show diminished explanatory power.

Model 2 shows stronger alignment with prior expectations. The inclusion of the capitalized R&D asset $RDA_{i,t}$ improves adjusted R^2 from 0.36 to 0.50, nearly equal to the main sample baseline. Notably, the coefficient on the R&D asset increases to 1.863 (from 1.26 in the main sample), indicating that markets place a greater valuation weight on unrecognized intangible assets when R&D intensity is high. Both earnings and misstatement coefficients remain significant, although their magnitudes are slightly lower.

Overall, these results offer support for the thesis's main findings. While the expectation was that R&D-intensive firms would exhibit substantially stronger valuation effects from capitalizing R&D, the observed amplification is modest.

4.3.3 Time Variation in Value Relevance – Upper Quartile

Tables 12 and 13 present five-year average coefficients from annual cross-sectional regressions for Models 1 and 2, restricted to the upper quartile of firms by R&D intensity. These results allow a comparison of how value relevance evolved over time in the most R&D-intensive firms.

Table 12: 5-year Average Annual Cross-Sectional OLS – R&D Intensity upper Quartile: Model 1

	Model 1					
	Independent Variables					
Dependent Variable	**Intercept**	$\boldsymbol{NI_{i,t}}$	$\boldsymbol{NI_{t,i}^{adj} - NI_{i,t}}$	$\boldsymbol{RDA_{i,t}}$	$\boldsymbol{adj.R^2}$	**N**
$\boldsymbol{P_{i,t}}$ *1994 – 1998*	10.085	6.822*** (29.871)	8.170*** (8.551)	-	0.440	1,737
$\boldsymbol{P_{i,t}}$ *1999 – 2003*	10.605	4.490*** (7.642)	8.864*** (6.891)	-	0.243	2,222
$\boldsymbol{P_{i,t}}$ *2004 – 2008*	8.619	5.937*** (8.247)	8.832*** (7.006)	-	0.395	2,300
$\boldsymbol{P_{i,t}}$ *2009 – 2013*	9.980	6.785*** (12.262)	9.598*** (10.990)	-	0.406	2,022
$\boldsymbol{P_{i,t}}$ *2014 – 2018*	13.098	7.545*** (19.439)	14.100*** (9.391)	-	0.367	1,586
$\boldsymbol{P_{i,t}}$ *2019 – 2023*	11.624	5.250*** (16.796)	20.546*** (16.150)	-	0.327	1,211

*T-statistics are reported in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10. All variables are scaled per share. Estimates are based on annual cross-sectional regressions; reported coefficients are time-series means.*

In Model 1, $NI_{t,i}^{adj} - NI_{i,t}$ remains significant and economically meaningful across all periods, ranging from 8.17 in 1994–1998 to a peak of 20.55 in 2019–2023. However, unlike in the main sample, the adjusted R^2 does not show a consistent upward trend, fluctuating between 0.24 and 0.44. This suggests that while the pricing relevance of R&D misstatement has increased in more recent years, the overall explanatory power of earnings alone in high-intensity firms remains somewhat volatile and context-dependent. This is surprising, as the explanatory power in this upper quartile does not consistently exceed that of the main sample. It suggests that while R&D adjustments remain relevant, earnings-based valuation signals may be noisier or more volatile in high R&D intensity firms.

Table 13: 5-year Average Annual Cross-Sectional OLS – R&D Intensity upper Quartile: Model 2

	Model 2					
	Independent Variables					
Dependent Variable	**Intercept**	$NI_{i,t}$	$NI_{t,i}^{adj} - NI_{i,t}$	$RDA_{i,t}$	$adj.R^2$	**N**
$P_{i,t}$ *1994 – 1998*	3.990	5.515*** (16.054)	7.766*** (13.536)	1.777*** (10.850)	0.558	1,737
$P_{i,t}$ *1999 – 2003*	5.071	4.277*** (11.923)	8.779*** (7.338)	1.750*** (16.522)	0.384	2,222
$P_{i,t}$ *2004 – 2008*	2.636	5.313*** (7.605)	7.290*** (6.447)	1.810*** (10.812)	0.566	2,300
$P_{i,t}$ *2009 – 2013*	3.872	5.807*** (11.731)	8.577*** (11.377)	1.600*** (9.109)	0.533	2,022
$P_{i,t}$ *2014 – 2018*	4.099	6.506*** (17.848)	11.655*** (10.462)	2.231*** (41.534)	0.502	1,586
$P_{i,t}$ *2019 – 2023*	4.531	5.524*** (11.444)	17.073*** (16.783)	2.009*** (9.045)	0.435	1,211

*T-statistics are reported in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10. All variables are scaled per share. Estimates are based on annual cross-sectional regressions; reported coefficients are time-series means.*

Model 2 strengthens this observation. The coefficient of $RDA_{i,t}$ is stable and consistently high across subperiods, ranging from 1.60 to 2.23, notably higher than in the main sample, where the average was around 1.26. Adjusted R^2 values in Model 2 are also more stable and robust, peaking at 0.566 in 2004–2008 and remaining above 0.50 in several periods. This partially confirms the original expectation, as the capitalized R&D asset consistently contributes stronger explanatory power in the upper quartile sample, even if not by a large margin.

The temporal patterns observed here underscore that the valuation relevance of R&D capitalization is not only persistent but has intensified over time, especially since 2010. Still, the effect is more modest than anticipated, and the gap in explanatory power between high and moderate R&D firms is narrower than theory might suggest.

5 Discussion

5.1 Interpretation of Main Findings

This study empirically examined whether capitalizing R&D expenditures improves the value relevance of accounting information in U.S. capital markets. Drawing on the framework established by Lev and Sougiannis (1996), the core objective was to assess whether treating R&D as an asset, rather than an immediate expense, enhances the explanatory power of price-earnings regressions in a US GAAP context. Two complementary models were used: Model 1 included reported earnings and an adjusted earnings measure, capturing the misstatement occurring due to not capitalizing R&D. Model 2 expanded the model with a capitalized R&D asset. Both pooled OLS and annual cross-sectional regressions were applied across two datasets: one comprising all firm-years (including imputed R&D values) and one restricted to observations where real R&D expenditures data were available.

As expected, the reported earnings remain a consistently strong and statistically significant determinant of market value across all specifications. This confirms the ongoing relevance of traditional earnings measures. However, the analysis also demonstrates that earnings alone do not fully capture firm value when intangible investments and R&D investments, in particular, are expensed under prevailing accounting rules. This is evidenced by the misstatement variable, which was not only significant but often greater in economic magnitude than the reported earnings themselves. This finding directly confirms the hypothesis outlined and prior findings in the literature, that uncapitalized R&D leads to underestimating firm value, and that investors respond to this gap when information is available.

Including the capitalized R&D asset in Model 2 confirms the expectations and further improves the explanatory power of the valuation models. The $RDA_{i,t}$ coefficient is consistently significant and stable across time in the reported-only sample. The model's adjusted R-squared increases remarkably, supporting the idea that capitalizing R&D captures value-relevant information that traditional accounting omits.

5.2 Classification of Results

This study confirms several key results from earlier literature while refining their scope. Most directly, it reaffirms the core findings of Lev and Sougiannis (1996) that capitalized R&D contributes incremental explanatory power to price regressions beyond reported earnings.

Building on this, it is important to highlight how this study expands upon prior work. While many studies exclusively focus on R&D-intensive firms, e.g., identified through SIC Codes and R&D intensity (Aboody & Lev, 1998; Lev & Sougiannis, 1996), the present analysis utilizes a broader, market-wide dataset for the main analysis that includes firms from all sectors. The persistence of value-relevant R&D effects in this wider sample suggests that the role of R&D

in valuation is not just industry-specific but has been a generalizable phenomenon within the observation period. This extension reinforces the argument that in today's knowledge-driven economy, intangible investments such as R&D are no longer confined to a narrow subset of industries but are increasingly central across firm types.

Notably, Lev and Sougiannis (1996) additionally conducted their analysis on the upper quartile of their firm in terms of R&D intensity (defined by the R&D capital to reported book value ratio), leading to even stronger results. This study replicates that robustness check using the updated dataset and methodology, focusing on the top quartile of firms by R&D capital to total assets. While capitalized R&D remains significantly value-relevant within this group, the magnitude of effects is only moderately higher than in the broader reported-only sample, with slightly lower explanatory power in some cases. These findings suggest that, contrary to expectations and prior literature, the pricing impact of R&D capitalization is not limited to the most R&D-intensive firms but is already meaningfully present across a broad cross-section of the market. This result strengthens the generalizability of the core findings while also indicating that high R&D intensity alone does not necessarily imply disproportionately more substantial valuation effects.

One possible explanation for this outcome is that such firms exhibit greater heterogeneity, higher uncertainty, or noisier earnings signals, which may offset the gains from more accurate accounting treatment. Nonetheless, the consistent significance and stronger R&D asset coefficient reaffirm that capitalizing R&D enhances valuation relevance, supporting its application across a broad spectrum of corporate contexts.

The findings are also consistent with Clausen and Hirth (2016), who argue that R&D is the most value-relevant among various types of intangibles. The robustness of the $RDA_{i,t}$ coefficient in this study, across pooled and cross-sectional regressions, and over time, supports their conclusion. Similarly, Peters and Taylor (2017) and Eisfeldt and Papanikolaou (2013) highlight the importance of firm-specific intangible investment in explaining market valuations. This study empirically validates that claim by showing that firm-specific R&D reporting, when capitalized appropriately, aligns closely with how markets value intangible-driven earnings potential.

At the same time, the findings extend the insights of Ciftci et al. (2014), who document a decrease in the value relevance of accounting metrics in intangible-intensive sectors. While the results confirm a decline in value relevance of reported earnings relative to capitalized R&D metrics, their absolute relevance remains strong and stable. Inherent in the results also for the upper quartile of R&D intensity, these findings are contrary to those of Cifti et al. (2014).

This interpretation is further reinforced by Lev and Zarowin's (1999) broader argument about the declining relevance of earnings. Their findings were made in a context where intangible investments were becoming increasingly dominant, but accounting practices had not evolved to reflect them. The present study shows that once R&D is capitalized using disclosed, firm-specific information, earnings retain substantial explanatory power, and markets respond positively to adjustments that make intangible investment more visible. In this sense, the study does not confirm the underlying concern of declining earnings relevance but updates it by showing a way to improve their informativeness.

Relatedly, Aboody and Lev (1998) provide an important contribution in support of capitalization by examining software firms permitted to capitalize development costs under SFAS 86. Their findings demonstrate that capitalized R&D is positively associated with market value and improves the predictive power of earnings. The parallels with the current study are clear. When capitalization is allowed under accounting standards, markets appear to respond accordingly. This thesis reinforces that insight, extending it beyond the software industry by applying a standardized capitalization and amortization procedure across sectors. It suggests that the principle holds that recognition of R&D enhances financial informativeness more generally.

While this study centers on R&D as a tractable and measurable intangible, the findings have broader implications. The persistent valuation effects observed mirror concerns raised in the wider literature on intangible capital, ranging from brand equity to organizational know-how, which remains unrecognized under conservative accounting regimes. As such, R&D serves as a representative case within a larger set of underreported value drivers in the modern firm. The results contribute to that broader discourse by showing how even limited reforms to recognition and measurement could meaningfully improve the informativeness of financial statements.

5.3 Time Variation and Economic Context

Beyond the average relationships uncovered in pooled and cross-sectional regressions, this study also investigates how the value relevance of earnings and capitalized R&D evolved over time. Using five-year subperiods and the yearly results from 1994 to 2023, the analysis examines how economic context and market conditions influence the value relevance of the examined variables.

The temporal evolution of R&D value relevance suggests that investor pricing of intangible assets is closely tied to broader macroeconomic conditions and structural shifts in the economy. The spike in the coefficients on capitalized R&D around 1999, for instance, aligns with the peak of the dot-com boom, when markets were heavily focused on technology and innovation, often valuing growth potential over fundamentals. This period reflects heightened investor sensitivity to forward-looking intangible indicators, even before many firms had achieved profitability.

In contrast, the sharp decline in R&D relevance during 2008 corresponds with the global financial crisis, when markets returned to conservative valuation practices and penalized uncertainty. In such risk-off environments, tangible assets and reported earnings tend to regain importance, while investments like R&D are discounted more heavily.

The most striking trend, however, is a steady and substantial increase in the relevance of capitalized R&D throughout the 2010s, following the financial crisis, culminating in a peak around 2020. This long-term rise aligns with the structural change in the economy, characterized by digital transformation, the dominance of intangibles, and investor adaptation to new forms of value creation. By the late 2010s, firms across various industries invested in innovation as a core strategic activity, and capital markets increasingly responded to these signals.

The peak in 2020, coinciding with the COVID-19 crisis, may seem counterintuitive at first. However, it can be interpreted as a continuation of the structural shift rather than a short-term anomaly. The pandemic accelerated trends such as digitalization and remote infrastructure, thereby intensifying investor focus on firms with intangible-intensive business models. As such, the increased relevance of R&D during this time may reflect investors' heightened demand for innovation-based resilience rather than a speculative overreaction.

The slight decline in R&D value relevance post-2020 could indicate a partial normalization as macroeconomic uncertainty and inflationary pressures emerged, or simply a plateau after a decade of rapid growth in intangible investment. Regardless, the overarching trend supports the interpretation that R&D is increasingly central to how investors evaluate firm value.

By examining these dynamics over time, the study contributes to a more nuanced understanding of the conditions under which capital markets price R&D. It demonstrates that investor reliance on earnings adjustments and intangible proxies is not static but varies in response to macroeconomic trends. This temporal dimension constitutes a key added value of this work.

5.4 Methodological Reflections and Limitations

5.4.1 Methodological Trade-Offs and Omitted Adjustments

While consistent with prior literature, several methodological choices in this study imply trade-offs and leave room for future refinement. First, the regressions do not include firm or industry fixed effects. These could have captured unobserved heterogeneity at the firm or sector level that may influence the relationship between accounting variables and stock prices. Likewise, the models do not explicitly control for firm size, which may affect both the scale of R&D investment and the interpretation of its significance. Incorporating a firm size proxy or examining the interaction of size with R&D variables could provide additional insights into how R&D value relevance varies across different firm sizes.

While the primary analysis of this study does not isolate firms by R&D intensity or apply sector-level adjustments to control for differences in innovation profiles, a targeted robustness check was conducted to address this limitation. Specifically, the study complements its broad-sample findings with an upper-quartile analysis based on the R&D capital to total assets ratio, replicating the subsample approach used by Lev and Sougiannis (1996). This enables the identification of firms with exceptionally high intangible intensity.

Nonetheless, no industry-level filtering or adjustment was applied to account for sector-specific capitalization eligibility, such as that of software firms (e.g., SIC 7372), which are permitted to capitalize R&D under SFAS 86. Treating these firms identically to others may introduce comparability issues due to differences in R&D reporting. While the main findings represent average effects across a heterogeneous set of firms, the inclusion of the high-intensity subsample provides a partial control for this heterogeneity, but does not capture all potential variation that might be revealed through sector-specific analyses.

Moreover, the study does not explore how R&D intensity has changed over time or varies systematically across sectors. Nor does it conduct firm-level time-series analysis that would allow tracking how R&D functions as a value driver within individual firms over multiple years.

Such analyses could uncover persistent or firm-specific learning effects in investor response to intangible investments.

On a structural level, the models are estimated using cross-sectional and pooled OLS, which do not account for dynamics or feedback effects. More sophisticated techniques, such as dynamic panel regressions or generalized method of moments (GMM), could control for potential endogeneity or persistence in earnings and valuation relationships. Additionally, the regressions do not incorporate interaction terms between R&D measures and macroeconomic or contextual variables, which could help identify conditional effects or nonlinearities.

The R&D capitalization methodology itself follows a fixed straight-line amortization schedule based on industry averages, without estimating firm-specific useful lives. While this enhances comparability and convenience, it may obscure idiosyncratic timing effects in how firms realize returns from innovation.

These methodological limitations do not undermine the study's core findings but suggest that further granularity, customization, or econometric sophistication may help sharpen and extend the results in future work.

5.4.2 Data Quality and Imputation Limitations

While this study tries to ensure a sufficient sample size while retaining data validity by including both a reported-only sample and an imputed sample, both approaches involve data-related limitations that affect generalizability and interpretation.

First, sample composition and disclosure bias may affect both datasets. The reported-only sample consists of 5,166 firm-year observations, smaller but cleaner than the imputed sample of 7,896. However, firms that consistently disclose R&D are often larger, more innovation-focused, and potentially more successful in their R&D efforts. This introduces a possible survivorship bias, as firms that failed or exited the market may be underrepresented. This limitation is not controlled for in this study.

Second, although outlier treatment was applied (using winsorizing at the 1st and 99th percentiles) on the raw variables before imputation and again on the regression variables before regression, both samples still contain extreme values to some extent. This is especially inherent in capitalized R&D and adjusted earnings. These values are not merely statistical noise. They may reflect aggressive accounting practices, sector-specific growth dynamics, or data anomalies. Winsorizing reduces noise but cannot eliminate distortion introduced by compounded outliers, particularly when volatile denominators, such as sales, scale R&D.

This also majorly affected the imputation process. The regression used to estimate missing R&D values was run on the entire COMPUSTAT/CRSP dataset. Even though winsorized at the 1st and 99th percentile level, that still included firm-year observations with potentially poor data quality and extreme values. Applying the industry pooling rule, which requires a minimum of only five firms per SIC-year group, may lead to imputation regressions with high heterogeneity within a small sample. Furthermore, for SIC groupings closer to the 2-digit level, the resulting peer-based estimates can reflect substantial heterogeneity in innovation strategies, cost structures, and disclosure norms due to the large number of firms included in these groups.

Additionally, firm size was not accounted for during the imputation process, which is significant given that large firms tend to invest more in R&D in absolute terms and may exhibit systematically different patterns in how R&D relates to valuation. Scaling R&D expenses with sales partly controls for firm size in the estimation step, but the imputed R&D values may remain biased either upward or downward, depending on the dominance of particular firm types within SIC groups. Combined with the COMPUSTAT database's known inconsistencies in R&D disclosure across time and firm size, these factors impose caution when interpreting the strength of findings based on imputed data.

As a result of these limitations, regression models estimated on the imputed sample produced weak or even counterintuitive results, including inconsistent coefficient signs and a lack of explanatory power for key variables such as the capitalized R&D asset. These distortions made the findings difficult to interpret and undermined the reliability of the imputed dataset for drawing conclusions about value relevance.

In sum, while the reported-only dataset offers more reliability, its narrower scope reduces coverage. The full dataset enhances generalizability but suffers from inferential noise due to limitations in imputation. This trade-off ultimately led to the decision to base the main empirical analysis on the reported-only dataset, prioritizing data quality and interpretability over broader sample size.

5.4.3 Interpretation and Generalizability

The findings of this study offer robust evidence for the value relevance of capitalized R&D. However, several interpretive limitations constrain how the results can be generalized or extended across contexts.

Most importantly, the results are rooted in the United States' accounting rules, where U.S. GAAP requires immediate expensing of internally generated R&D. While this creates a clean setting for testing capitalization adjustments ex post, it limits generalizability to jurisdictions with different rules, such as IFRS, which permits capitalization of development costs under specific conditions under IAS 38. The valuation effects observed here might differ in regulatory environments where intangible recognition differs.

The analysis also does not distinguish between investor types or behavioral patterns in interpreting R&D adjustments. Although the statistical results suggest that markets respond to capitalized R&D and adjusted earnings signals, no direct evidence is presented on how investors perceive or act on these adjustments. Future research may need to incorporate survey data, analyst forecast reactions, or trading volume analysis to assess how such adjustments are understood in practice.

In addition, the study does not incorporate macroeconomic variables or contextual controls that could influence the valuation of R&D across business cycles. Although temporal variation was analyzed, the role of interest rates, inflation expectations, or monetary shocks was not explicitly modeled. Likewise, the regressions do not differentiate across industries or sectors, potentially masking differences in how innovation is priced in pharmaceuticals versus software, for example.

Another interpretive limitation stems from the contemporaneous modeling approach. The thesis assumes that R&D is valued in the same year it is expensed or capitalized. However, economic returns to innovation are rarely immediate. By not including lagged dependent variables or multi-year panels, the analysis may understate or misattribute longer-term effects of R&D on firm value.

Lastly, the comparative strength of results in the reported-only sample must still be interpreted with care. As noted earlier, this sample likely includes firms with a generally higher R&D intensity that are more transparent or bigger in size. If so, the stronger results observed here may partially reflect sample selection bias, rather than purely informational effects.

Despite these limitations, the study offers valuable insights into the evolving role of intangibles in firm valuation, while also making explicit the methodological and contextual boundaries within which these conclusions hold.

5.5 Implications and Future Research

The empirical results have several practical implications for analysts, standard setters, and capital market participants. Most notably, they underscore that capitalizing R&D expenditures can significantly improve the explanatory power of valuation models. For financial analysts and institutional investors, this suggests that integrating an internally constructed R&D asset into pricing frameworks yields a more accurate representation of firm value. The findings are particularly relevant in an era where traditional book metrics are increasingly detached from market valuations, as similarly highlighted by Ciftci et al. (2014) and Peters and Taylor (2017).

For accounting standard setters, the study provides empirical support for calls to reform the treatment of R&D under U.S. GAAP and similar frameworks. Currently, most internally developed R&D is expensed immediately, regardless of its future economic benefits. The persistent significance of capitalized R&D in the analyses, not just in levels but also in its increasing relevance over time, suggests that current expense rules systematically understate the value of intangible-intensive firms. These results mirror the conceptual critique raised by the literature (Lev, 2003; Lev & Zarowin, 1999, 1999; Mortensen et al., 1997) arguing that the historical cost model has failed to evolve alongside the knowledge economy. A more nuanced recognition approach, perhaps modeled after SFAS 86 for software development (as discussed in Aboody and Lev (1998)), could improve transparency and alignment between financial statements and investor information needs.

From a capital markets perspective, the study reinforces that a lack of R&D disclosure or inadequate recognition of R&D can distort value signals. Investors appear capable of pricing R&D even without formal recognition, as shown by the consistent effect of the R&D adjusted variables shown in the Models. However, doing so might increase reliance on estimation and increase informational asymmetries. This finding aligns with insights from Lev and Zarowin (1999), who documented declining earnings relevance as intangibles rose in importance, highlighting how adjustments like R&D capitalization may restore financial reporting's predictive value.

Several extensions can be proposed for future research. First, while R&D is among the most measurable intangible assets, it is only one component of a broader spectrum that includes intangibles such as brand equity, customer capital, and organizational know-how. Studies such as Clausen and Hirth (2016) and Eisfeldt and Papanikolaou (2013) show that these categories may also carry explanatory power if appropriately proxied. Extending the capitalization framework used in this thesis to other intangible domains could provide a richer view of how firms create and retain value.

Second, a promising approach lies in examining cross-country differences in the recognition and pricing of R&D. For instance, under IFRS, capitalization of development expenditures is mandatory under certain conditions, offering a contrast with the U.S. GAAP expensing rules. Comparative studies could test whether market responses differ when capitalization is allowed rather than inferred.

Methodologically, future research may also benefit from applying dynamic panel models or GMM estimators to control for potential omitted variable bias and serial correlation. The current study uses pooled and annual cross-sectional regressions, which are robust and replicable, but more advanced techniques could test whether the effects hold in alternative specifications or under different market structures.

Finally, behavioral finance literature could be utilized to examine how investors interpret high earnings misstatements and capitalized R&D signals. This means whether firms with significant differences between reported and adjusted earnings are rewarded or penalized, and under what conditions. Such work could provide insights into whether markets view R&D capitalization as a signal of long-term value creation or potential earnings management.

In sum, this study not only contributes to the empirical literature on the value relevance of R&D but also raises new questions about how to best recognize, model, and price intangible assets in capital markets, where intangible value drivers are increasingly dominant.

6 Conclusion

This study examined whether capitalizing R&D expenditures enhances the value relevance of financial information in U.S. capital markets and how this relationship evolves over time. Drawing on a 30-year dataset and building on the framework of Lev and Sougiannis (1996), the analysis demonstrates that capitalizing R&D consistently improves the explanatory power of valuation models when based on firm-reported data. This effect is statistically robust and intensified in recent years, aligning with the economy's ongoing shift toward intangible-intensive production.

The findings confirm that investors are increasingly valuing R&D as an unrecognized asset. This study contributes to the broader conversation about how accounting systems should evolve in response to structural economic change by demonstrating that even a standardized capitalization approach can increase value relevance.

Beyond replicating earlier results in a more recent setting, the study adds value by introducing a temporal perspective, identifying when and under what conditions capitalized R&D becomes more relevant.

While methodological and data-related limitations remain, the study makes a valuable contribution to both the academic debate and financial industry practitioners. For investors and analysts, the results support adjustments when analyzing reported financials to reflect the value relevance of R&D investments accurately. For standard setters, they add empirical weight to arguments for reconsidering the treatment of internally generated intangibles under U.S. GAAP. More broadly, the thesis reaffirms that accounting's relevance depends on its ability to reflect the actual sources of firm value, and that R&D plays an increasingly visible role in that valuation process.

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Appendix

Appendix

Appendix 1: Industry Amortization Rate Mapping

SIC Codes	Industry *(Lev and Sougiannis, 1996)*	δ *(Li and Hall, 2020)*
2830	Pharmaceuticals	11.2%
2831	Pharmaceuticals	11.2%
2833	Pharmaceuticals	11.2%
2834	Pharmaceuticals	11.2%
2835	Pharmaceuticals	11.2%
2836	Pharmaceuticals	11.2%
3570	Computers and peripheral equipment	36.3%
3571	Computers and peripheral equipment	36.3%
3572	Computers and peripheral equipment	36.3%
3573	Computers and peripheral equipment	36.3%
3574	Computers and peripheral equipment	36.3%
3575	Computers and peripheral equipment	36.3%
3576	Computers and peripheral equipment	36.3%
3576	Communication equipment	19.2%
3577	Computers and peripheral equipment	36.3%
3578	Computers and peripheral equipment	36.3%
3579	Computers and peripheral equipment	36.3%
3585	Motor vehicles, bodies and trailers, and parts	73.3%
3661	Semiconductor	22.6%
3661	Communication equipment	19.2%
3662	Semiconductor	22.6%
3663	Semiconductor	22.6%
3663	Communication equipment	19.2%
3664	Semiconductor	22.6%
3665	Semiconductor	22.6%
3666	Semiconductor	22.6%
3669	Semiconductor	22.6%
3669	Communication equipment	19.2%
3670	Semiconductor	22.6%
3671	Semiconductor	22.6%
3672	Semiconductor	22.6%
3673	Semiconductor	22.6%
3674	Semiconductor	22.6%
3675	Semiconductor	22.6%
3676	Semiconductor	22.6%
3677	Semiconductor	22.6%
3678	Semiconductor	22.6%
3679	Semiconductor	22.6%
3679	Communication equipment	19.2%

3680	Computers and peripheral equipment	36.3%
3681	Computers and peripheral equipment	36.3%
3682	Computers and peripheral equipment	36.3%
3683	Computers and peripheral equipment	36.3%
3684	Computers and peripheral equipment	36.3%
3685	Computers and peripheral equipment	36.3%
3686	Computers and peripheral equipment	36.3%
3687	Computers and peripheral equipment	36.3%
3688	Computers and peripheral equipment	36.3%
3689	Computers and peripheral equipment	36.3%
3695	Computers and peripheral equipment	36.3%
3711	Motor vehicles, bodies and trailers, and parts	73.3%
3713	Motor vehicles, bodies and trailers, and parts	73.3%
3714	Motor vehicles, bodies and trailers, and parts	73.3%
3715	Motor vehicles, bodies and trailers, and parts	73.3%
3716	Motor vehicles, bodies and trailers, and parts	73.3%
3720	Aerospace product and parts	33.9%
3721	Aerospace product and parts	33.9%
3724	Aerospace product and parts	33.9%
3728	Aerospace product and parts	33.9%
3760	Aerospace product and parts	33.9%
3812	Navigational, measuring, electromedical, and control instruments	32.9%
3822	Navigational, measuring, electromedical, and control instruments	32.9%
3823	Navigational, measuring, electromedical, and control instruments	32.9%
3825	Navigational, measuring, electromedical, and control instruments	32.9%
3826	Navigational, measuring, electromedical, and control instruments	32.9%
3829	Navigational, measuring, electromedical, and control instruments	32.9%
3842	Navigational, measuring, electromedical, and control instruments	32.9%
3844	Navigational, measuring, electromedical, and control instruments	32.9%
3845	Navigational, measuring, electromedical, and control instruments	32.9%
7370	Computer system design	48.9%
7371	Computer system design	48.9%
7372	Software	30.8%
7373	Computer system design	48.9%
8731	Scientific research and development	29.5%

Source: Data compiled and mapped by author, based on Lev and Sougiannis (1996) and Li and Hall (2020)

Appendix 2: Pooled OLS – Imputed sample

Dependet Variable		Intercept	$NI_{i,t}$	$NI_{t,i}^{adj} - NI_{i,t}$	$RDA_{i,t}$	$adj.R^2$	N
		Independent Variables					
1.	$P_{i,t}$	20.289	4.289***	0.0001**	-	0.22	73,340
			(11.49)	(-3.43)			
2.	$P_{i,t}$	20.288	4.289***	-0.0003*	0.00001	0.22	73,340
			(11.49)	(-1.70)	(-0.43)		

*T-statistics are reported in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10. All variables are scaled per share. Estimates are based on pooled OLS regressions with robust standard errors.*

Appendix 3: Annual Cross-sectional OLS – Imputed sample

Dependent Variable		Intercept	$NI_{i,t}$	$NI_{t,i}^{adj} - NI_{i,t}$	$RDA_{i,t}$	$adj.R^2$	N
		Independent Variables					
1.	$P_{i,t}$	20.262	5.054***	0.000	-	0.27	73,340
			(16.487)	(-0.438)			
2.	$P_{i,t}$	20.231	5.049***	0.012***	0.003***	0.27	73,340
			(16.492)	(4.246)	(5.405)		

*T-statistics are reported in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10. All variables are scaled per share. Estimates are based on annual cross-sectional regressions; reported coefficients are time-series means.*

Appendix 4: 5y Average Annual Cross-sectional OLS – Imputed sample: Model 1

Model 1

	Independent Variables					
Dependent Variable	**Intercept**	$NI_{i,t}$	$NI_{t,i}^{adj} - NI_{i,t}$	$RDA_{i,t}$	$adj.R^2$	**N**
$P_{i,t}$	14.745	5.595***	0.000***	-	0.301	14,124
1994 – 1998		(12.239)	-(5.271)			
$P_{i,t}$	15.625	4.028***	0.000	-	0.222	13,908
1999 – 2003		(7.399)	-(0.650)			
$P_{i,t}$	16.086	5.438***	0.000	-	0.359	13,683
2004 – 2008		(7.315)	-(0.036)			
$P_{i,t}$	19.134	6.498***	-0.001***	-	0.355	11,750
2009 – 2013		(15.910)	-(4.430)			
$P_{i,t}$	26.255	5.867***	-0.002**	-	0.266	10,666
2014 – 2018		(8.458)	-(1.747)			
$P_{i,t}$	29.726	2.896***	0.002	-	0.134	9,209
2019 – 2023		(7.293)	(0.628)			

*T-statistics are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All variables are scaled per share. Estimates are based on annual cross-sectional regressions; reported coefficients are time-series means.*

Appendix 5: 5y Average Annual Cross-sectional OLS – Imputed sample: Model 2

	Model 2					
	Independent Variables					
Dependent Variable	**Intercept**	$NI_{i,t}$	$NI_{t,i}^{adj} - NI_{i,t}$	$RDA_{i,t}$	$adj.R^2$	**N**
$P_{i,t}$ *1994 – 1998*	14.735	5.593*** (12.199)	0.007*** (1.109)	0.001 (1.135)	0.301	14,124
$P_{i,t}$ *1999 – 2003*	15.588	4.022*** (7.352)	0.012* (1.675)	0.002* (1.671)	0.223	13,908
$P_{i,t}$ *2004 – 2008*	16.065	5.438*** (7.327)	0.006 (1.402)	0.001 (1.476)	0.360	13,683
$P_{i,t}$ *2009 – 2013*	19.115	6.486*** (15.867)	0.019*** (5.748)	0.003*** (6.038)	0.356	11,750
$P_{i,t}$ *2014 – 2018*	26.198	5.857*** (8.457)	0.027*** (2.561)	0.005*** (2.662)	0.267	10,666
$P_{i,t}$ *2019 – 2023*	29.686	2.898*** (7.286)	0.002 (0.573)	0.003*** (4.327)	0.135	9,209

*T-statistics are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All variables are scaled per share. Estimates are based on annual cross-sectional regressions; reported coefficients are time-series means.*

Appendix 6: Yearly Annual Cross-Sectional OLS – Model 1 (1994–2023)

Model 1

Dependent Variable	Intercept	$NI_{i,t}$	$NI_{t,i}^{adj} - NI_{i,t}$	$RDA_{i,t}$	$adj. R^2$	N
	Independent Variables					
$P_{i,t}$ *1994*	9.943	8.108*** (21.549)	7.432*** (7.344)	-	0.549	1,439
$P_{i,t}$ *1995*	11.175	8.294*** (23.319)	6.543*** (6.320)	-	0.503	1,534
$P_{i,t}$ *1996*	10.612	9.033*** (23.930)	8.337*** (9.035)	-	0.540	1,603
$P_{i,t}$ *1997*	12.131	9.698*** (25.380)	8.349*** (8.214)	-	0.499	1,620
$P_{i,t}$ *1998*	10.373	7.873*** (22.860)	10.996*** (9.092)	-	0.390	1,566
$P_{i,t}$ *1999*	14.267	6.186*** (15.895)	16.130*** (8.979)	-	0.255	1,610
$P_{i,t}$ *2000*	11.055	6.472*** (23.809)	9.341*** (6.603)	-	0.334	1,639
$P_{i,t}$ *2001*	14.020	7.458*** (23.742)	11.420*** (8.889)	-	0.423	1,672
$P_{i,t}$ *2002*	11.215	6.350*** (23.594)	7.941*** (8.323)	-	0.437	1,684
$P_{i,t}$ *2003*	14.575	8.820*** (23.349)	9.358*** (6.759)	-	0.490	1,812
$P_{i,t}$ *2004*	11.530	10.206*** (28.312)	9.441*** (9.629)	-	0.581	1,906
$P_{i,t}$ *2005*	12.875	10.840*** (29.281)	10.808*** (9.202)	-	0.578	1,880
$P_{i,t}$ *2006*	13.089	10.837*** (30.639)	9.347*** (8.035)	-	0.598	1,812
$P_{i,t}$ *2007*	11.101	9.424*** (27.092)	7.429*** (5.393)	-	0.555	1,699
$P_{i,t}$ *2008*	9.061	5.313*** (22.783)	6.666*** (6.375)	-	0.460	1,508
$P_{i,t}$ *2009*	14.071	8.633*** (23.994)	7.345*** (5.469)	-	0.483	1,568
$P_{i,t}$ *2010*	13.435	10.361*** (25.627)	8.466*** (7.170)	-	0.506	1,585
$P_{i,t}$ *2011*	12.041	10.130*** (27.130)	6.162*** (4.729)	-	0.541	1,514

Model 1

Dependent Variable	Intercept	$NI_{i,t}$	$NI_{t,i}^{adj} - NI_{i,t}$	$RDA_{i,t}$	$adj. R^2$	N
	Independent Variables					
$P_{i,t}$ *2012*	13.644	11.078*** (32.523)	10.149*** (7.820)	-	0.578	1,458
$P_{i,t}$ *2013*	16.558	11.523*** (28.171)	12.434*** (7.109)	-	0.582	1,441
$P_{i,t}$ *2014*	16.482	12.506*** (31.681)	14.361*** (7.753)	-	0.590	1,416
$P_{i,t}$ *2015*	16.540	11.248*** (23.953)	13.677*** (6.980)	-	0.504	1,355
$P_{i,t}$ *2016*	18.734	11.802*** (26.175)	16.360*** (8.350)	-	0.515	1,317
$P_{i,t}$ *2017*	20.246	11.673*** (25.106)	19.967*** (7.873)	-	0.465	1,259
$P_{i,t}$ *2018*	17.760	11.043*** (24.767)	21.698*** (9.413)	-	0.472	1,182
$P_{i,t}$ *2019*	15.143	8.336*** (20.107)	26.203*** (10.222)	-	0.426	1,123
$P_{i,t}$ *2020*	26.323	10.264*** (20.088)	29.958*** (9.357)	-	0.392	1,052
$P_{i,t}$ *2021*	18.922	8.955*** (17.417)	27.439*** (8.196)	-	0.375	1,076
$P_{i,t}$ *2022*	18.020	9.102*** (19.935)	22.317*** (9.159)	-	0.422	1,062
$P_{i,t}$ *2023*	19.469	10.616*** (20.456)	21.357*** (7.400)	-	0.477	917

*T-statistics are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All variables are scaled per share. Estimates are based on annual cross-sectional regressions; reported coefficients are time-series means.*

Appendix 7: Yearly Annual Cross-Sectional OLS – Model 2 (1994–2023)

Model 2

Dependent Variable	**Independent Variables**								
	Intercept	$NI_{i,t}$		$NI_{t,i}^{adj} - NI_{i,t}$		$RDA_{i,t}$		$adj.R^2$	**N**
$P_{i,t}$ *1994*	7.676	7.753 (21.459)	***	5.152 (5.591)	***	1.313 (9.802)	***	0.590	1,439
$P_{i,t}$ *1995*	9.361	7.753 (21.812)	***	5.390 (5.874)	***	1.143 (7.199)	***	0.527	1,534
$P_{i,t}$ *1996*	8.184	8.428 (23.498)	***	5.979 (7.227)	***	1.555 (9.234)	***	0.581	1,603
$P_{i,t}$ *1997*	10.220	9.266 (24.312)	***	6.327 (6.780)	***	1.243 (6.712)	***	0.518	1,620
$P_{i,t}$ *1998*	7.853	7.581 (23.073)	***	8.246 (7.998)	***	1.502 (8.423)	***	0.427	1,566
$P_{i,t}$ *1999*	11.236	5.852 (15.301)	***	13.926 (8.487)	***	1.702 (7.856)	***	0.289	1,610
$P_{i,t}$ *2000*	9.065	6.222 (23.986)	***	8.203 (6.252)	***	1.163 (5.848)	***	0.356	1,639
$P_{i,t}$ *2001*	11.320	7.530 (25.004)	***	9.869 (9.414)	***	1.454 (8.873)	***	0.461	1,672
$P_{i,t}$ *2002*	9.195	6.488 (24.020)	***	6.614 (8.380)	***	1.098 (7.852)	***	0.468	1,684
$P_{i,t}$ *2003*	11.766	8.993 (24.886)	***	7.845 (6.474)	***	1.477 (8.911)	***	0.525	1,812
$P_{i,t}$ *2004*	10.138	10.165 (28.370)	***	8.132 (9.661)	***	0.818 (5.354)	***	0.591	1,906
$P_{i,t}$ *2005*	11.189	10.858 (29.748)	***	9.074 (8.628)	***	0.989 (6.390)	***	0.589	1,880
$P_{i,t}$ *2006*	11.661	10.784 (30.903)	***	7.752 (7.638)	***	0.859 (5.916)	***	0.607	1,812
$P_{i,t}$ *2007*	9.235	9.405 (27.452)	***	5.032 (3.877)	***	1.072 (5.605)	***	0.572	1,699
$P_{i,t}$ *2008*	7.897	5.254 (22.792)	***	5.492 (5.674)	***	0.614 (5.329)	***	0.472	1,508
$P_{i,t}$ *2009*	11.227	8.558 (24.411)	***	6.164 (5.234)	***	1.356 (9.592)	***	0.519	1,568
$P_{i,t}$ *2010*	12.525	10.204 (25.031)	***	7.788 (6.902)	***	0.486 (3.348)	***	0.509	1,585
$P_{i,t}$ *2011*	11.586	10.082 (26.889)	***	5.722 (4.553)	***	0.243 (1.471)		0.542	1,514

Model 2

Dependent Variable	Intercept	$NI_{i,t}$	$NI_{t,i}^{adj} - NI_{i,t}$	$RDA_{i,t}$	$adj. R^2$	N
	Independent Variables					
$P_{i,t}$ *2012*	13.033	11.029 *** (32.134)	9.594 *** (7.720)	0.314 ** (2.103)	0.579	1,458
$P_{i,t}$ *2013*	14.313	11.405 *** (28.320)	10.401 *** (6.377)	1.116 *** (6.036)	0.593	1,441
$P_{i,t}$ *2014*	14.218	12.337 *** (31.146)	12.809 *** (7.452)	1.122 *** (5.703)	0.600	1,416
$P_{i,t}$ *2015*	13.609	11.057 *** (23.776)	11.227 *** (5.632)	1.395 *** (5.338)	0.522	1,355
$P_{i,t}$ *2016*	14.443	11.790 *** (26.900)	12.748 *** (6.942)	1.925 *** (8.588)	0.546	1,317
$P_{i,t}$ *2017*	15.723	11.670 *** (25.729)	16.482 *** (7.212)	2.048 *** (7.819)	0.498	1,259
$P_{i,t}$ *2018*	14.943	10.928 *** (24.585)	17.767 *** (7.889)	1.423 *** (5.591)	0.487	1,182
$P_{i,t}$ *2019*	11.971	8.340 *** (20.616)	21.478 *** (8.462)	1.515 *** (6.519)	0.447	1,123
$P_{i,t}$ *2020*	22.623	10.152 *** (20.069)	25.289 *** (7.961)	1.808 *** (5.771)	0.412	1,052
$P_{i,t}$ *2021*	15.395	8.682 *** (17.304)	20.523 *** (5.748)	2.057 *** (5.956)	0.403	1,076
$P_{i,t}$ *2022*	15.793	8.934 *** (19.494)	18.387 *** (7.414)	1.256 *** (4.440)	0.434	1,062
$P_{i,t}$ *2023*	15.699	10.724 *** (21.285)	17.981 *** (6.845)	1.722 *** (6.674)	0.503	917

*T-statistics are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All variables are scaled per share. Estimates are based on annual cross-sectional regressions; reported coefficients are time-series means.*