The Impact of Intangible Investment on the Relative Importance of Firm-Specific Factors versus Market- and Industry-Level Factors in the Determination of Firm-Level Earnings

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Abstract

We examine the effect of intangible investment on earnings non-commonality, defined as the extent to which a firm's earnings performance is determined by firm-specific factors versus market- and industry-wide factors. Such insight is important in determining the appropriate weight to place on each of these factors when forecasting a firm's earnings. We measure earnings non-commonality as the unexplained portion (i.e., 1 minus the R^2) from firm-specific regressions of quarterly return on assets (ROA) on market- and industry-level ROA indices. Higher levels of our non-commonality measure are consistent with firm-level earnings that are more dependent on firm-specific factors as opposed to market and industry factors. For a sample of U.S. firms over the 1980 to 2006 period, we find that earnings non-commonality is positively associated with a firm's intangible asset intensity. This finding is consistent with the resource-based view (RBV) of the firm, which posits that intangible investments allow firms to differentiate themselves economically from their rivals. We also find that separable recognized intangible assets contribute more to earnings non-commonality than either goodwill or R&D investments, perhaps because separable recognized intangibles are more likely to arise from contractual or legal rights and, therefore, may be less susceptible to expropriation by rival firms, which might lead to commonalities in firms' earnings performance. Finally, we find that the positive impact of R&D investment on earnings non-commonality is significantly greater for those industries where patents and other legal mechanisms are most effective in protecting R&D. This result suggests that the success of intangible investment as part of a differentiation strategy depends largely on the effectiveness of mechanisms used to protect intangible investments from expropriation.

Keywords: Earnings non-commonality; intangible assets; appropriability.
Data availability: The data are available from public sources identified in the text.

1. Introduction

Past research finds that the earnings of individual firms comove or share, to varying degrees, commonalities with market- and industry-wide earnings (e.g., Ball and Brown 1967; Gonedes 1973; Magee 1974; Schmalensee 1985; Rumelt 1991; Mauri and Michaels 1998; McGahan and Porter 1997, 2002). Therefore, forecasting an individual firm's earnings requires appropriately weighting market-level, industry-level as well as firm-specific factors (Gonedes 1973; Fairfield et al. 2009). Consistent with this notion, Kini et al. (2009) find that analyst forecast accuracy increases when analysts structure their activities based on the degree of comovement in fundamentals among firms within a country or an industry. However, there is little evidence on what makes firm-specific factors relatively more or less important than market- and industry-level factors in determining an individual firm's earnings despite the importance of such insight for accurately forecasting a firm's earnings. In this study, we examine the effect of intangible investment on earnings non-commonality, defined as the extent to which a firm's earnings performance is determined by firm-specific factors rather than market- and/or industry-level factors.

Consistent with the accounting and finance literature (e.g., Magee 1974), we use the term "earnings non-commonality" to refer to the relative importance of firm-specific factors in determining the firm's earnings performance. Specifically, earnings non-commonality refers to the idiosyncratic or residual component of firm-level earnings that is not explained by industry or market earnings.

We focus on intangible resources because their theoretical properties are likely to be relevant in determining the degree of non-commonality in firm-level earnings. In particular, prior accounting research argues that earnings non-commonality is likely to be a product of a firm's intangible resources and its unique capabilities (Cyert 1967; Williams 1967; Piotroski and

Roulstone 2004; Elgers et al. 2004; Palepu et al. 2007). This conjecture is consistent with the resource-based view (RBV) of the firm as articulated in the strategy literature, which posits that investments in intangible assets are critical drivers of a successful economic differentiation strategy designed to create sustainable advantages over rival industry firms (e.g., Lippman and Rumelt 1982; Rumelt 1984; Itami 1987; Dierickx and Cool 1989; Barney 1991). Alternatively, the industrial organization paradigm contends that intangible resources are particularly susceptible to expropriation (or imitation) by rivals because they are, to varying degrees, non-rival and non-excludable. To the extent that intangible assets behave like public goods from which multiple firms can benefit, intangible investments could lead to greater comovement in firm profitability. Given these contrasting (though not mutually exclusive) perspectives, we are motivated to investigate the relation between intangible investments and non-commonality in firm-level earnings.

Following prior research (e.g., Morck et al. 2000; Elgers et al. 2004; Piostroki and Roulstone 2004), we measure earnings non-commonality as the log transformation of 1 minus the R^2 from firm-specific regressions of quarterly return on assets (ROA) on market- and industry-level ROA indices.[1] Higher (lower) levels of the non-commonality measure are consistent with firm-level earnings that are more (less) dependent on firm-specific factors. If intangible resources lead to economic differentiation as posited by the resource-based view (RBV), then we expect to find a positive relation between the level of intangible investment and our earnings non-commonality measure. On the other hand, if intangible resources behave more as public goods from which rivals can readily benefit, then we expect to find a negative relation between the level of intangible investment and the residual component of firm-level earnings.

[1]As discussed in Section 3.1, we adjust reported earnings and asset measures for implicit R&D capitalization when calculating quarterly ROA.

For a sample of U.S. firms over the 1980 to 2006 period, we find a positive relation between a firm's intangible asset intensity and earnings non-commonality. Therefore, our results indicate that the resource-based view of intangible resources dominates for our sample. We also examine the individual contribution of various classes of intangible investments — namely, goodwill, separable recognized intangible assets (other than goodwill), and the estimated unamortized cost of current and past R&D investment. We find that all three forms of intangibles contribute positively to the firm-specific component of earnings and that separable recognized intangibles contribute more to earnings non-commonality than either goodwill or R&D investment. This finding may be attributable to the fact that separable recognized intangibles are more likely to arise from contractual or legal rights and, therefore, may be less susceptible to expropriation by rivals, which might lead to commonalities in firms' earnings performance.

Prior research on R&D spillovers (e.g., Arrow 1962; Jaffe 1986; Levin et al. 1987; Cockburn and Griliches 1988; Davis 2001) suggests that our finding that R&D has a smaller association with earnings commonality relative to separable recognized intangibles is due to the greater susceptibility of R&D to expropriation or imitation by rival firms, which limits the degree to which R&D leads to economic differentiation. To provide insight on the plausibility of this interpretation, we directly examine the effect of legal property rights mechanisms on the extent to which R&D investment contributes to earnings non-commonality. We find a significantly positive relation between R&D investment and earnings non-commonality only in those industries where patents and other legal mechanisms are most effective in protecting R&D innovations. This result lends more direct support to the notion that appropriability conditions affect the extent to which intangible investments lead to economic differentiation.

In supplemental analyses, we find that intangible asset intensity in total as well as goodwill intensity and separable recognized asset intensity individually are positively related to non-commonality in stock returns, similar to their associations with earnings non-commonality. The fact that these associations are apparent in a stock return-based measure highlights the economic significance of our earnings-based results. In contrast to our earnings-based tests, however, we find that R&D intensity is negatively related to returns non-commonality. This result is consistent with the extensive literature on R&D spillovers and suggests that, even though R&D allows firms to economically differentiate themselves in the short run (as demonstrated by our earnings non-commonality tests), investors anticipate R&D to engender commonalities among firms in the long run. Finally, we document that the intensity and type of intangible assets a firm invests in affect the performance of the market- and industry-based profitability forecast models examined by Fairfield et al. (2009). This evidence demonstrates the implications of our findings for the relative importance of market-wide and industry-wide information when forecasting an individual firm's earnings.

Our study makes several contributions to the accounting literature. First, we extend the limited evidence on the underlying determinants of earnings non-commonality. Specifically, we provide previously undocumented evidence that intangible investment leads to firm-level earnings that are less dependent on common market and industry factors. This finding has implications for forecasting an individual firm's earnings since such forecasts rely on a combination of macroeconomic, industry-level, and firm-specific information. Our finding that intangible investment leads to earnings that are less dependent on market and industry factors suggests that firm-specific information is likely to be of greater importance in forecasting the earnings of intangible-intensive firms.

Second, our study complements prior research on the relation between intangible investment and various properties of accounting earnings. While prior studies document the effect of intangible investment on earnings persistence (Villalonga 2004) and earnings volatility (Kothari et al. 2002), our results show that intangible investment has a significant impact on earnings non-commonality—an important determinant of several accounting and market phenomena.[2] Third, our study provides empirical evidence on the extent to which the resource-based view versus the public-goods view of intangibles is most descriptive, which should be of interest to academics seeking to better understand the economic properties of intangible investments.

In addition, our evidence on the economic properties of intangibles is relevant to assessing the validity of standard setters' concerns about the lack of controllability of intangible assets. The belief that an entity cannot fully control its intangible resources (in addition to the perceived uncertainty surrounding the future benefits of such resources) has contributed to standard setters' reluctance to recognize intangible assets except in limited circumstances. Specifically, the recognition of intangible assets has been limited to the subset of valuable economic intangibles for which excludable and legally enforceable control rights exist (see Lev 2001; Maines et al. 2003; Basu and Waymire 2008; and Skinner 2008 for further discussion). Our evidence that intangible investments contribute positively to the idiosyncratic component of earnings suggests that intangible investments do not act primarily as pure public goods and, hence, may alleviate concerns about the extent to which intangible assets suffer from a lack of

[2] Prior studies document that commonality in earnings is an important determinant of several accounting and market phenomena such as stock return comovement (Morck et al. 2000; Piotroski and Roulstone 2004; Elgers et al. 2004; Ball et al. 2009), management disclosure (Gong et al. 2009; Kimbrough and Wang 2009), the structure of analyst research portfolios and analyst forecast accuracy (De Franco et al. 2009; Kini et al. 2009), and the structure of institutional investors' stock portfolios (Engelberg et al. 2009).

controllability. Nonetheless, the differential results for recognized intangibles versus R&D capital, particularly in the returns non-commonality tests, suggest that the criteria standard setters have mandated for recognizing intangible assets have succeeded in identifying those intangibles that are most controllable (i.e., those that behave least like public goods) and that concern about the controllability of R&D investments may be justified.

Finally, evidence on the economic properties of intangibles is also relevant to managers seeking to appropriate the full benefits of these resources. Our basic result is consistent with the conjecture that intangible investment can be a successful element of a firm's differentiation strategy. However, our finding that the relation between R&D investment and earnings non-commonality is a function of the effectiveness of legal protections for R&D implies that the success of intangible investment as part of a differentiation strategy depends largely on the strength of the mechanisms used to protect intangible investments from expropriation.

The remainder of this study proceeds as follows. Section 2 discusses related past research and sets forth the research questions examined in this study. Section 3 discusses the research design. Section 4 describes the sample. Section 5 discusses the empirical results and Section 6 concludes.

2. Background, theoretical development, and research questions

2.1 Background

Prior research documents significant commonalities between firm-level earnings and macroeconomic and industry-wide factors. In particular, Ball and Brown (1967) and Magee (1974) demonstrate that firm-level earnings vary significantly with average market-level and industry-level earnings. Schmalensee (1985) and McGahan and Porter (1997, 2002) also find that industry factors contribute significantly to the variation in firm profitability. Relatedly, using principal-components analysis, Ball et al. (2009) find that firm-level earnings contain a substantial systematic component.

Recent evidence suggests that information intermediaries such as analysts and institutional investors—whose work relies critically on the ability to accurately forecast earnings and other economic outcomes for the firms they follow—structure their activities based on the degree of commonality in firm fundamentals, presumably to exploit scale economies in information acquisition for firms facing similar economic forces. For example, among U.S. institutions, Kini et al. (2009) find that analysts are more likely to specialize within an industry (country) as the commonality or comovement of fundamentals within that industry (country) increases. Further, Kini et al. (2009) find that analyst specialization at the industry and country levels leads to significant improvements in earnings forecast accuracy. Similarly, De Franco et al. (2009) find that the commonality of firm-level earnings and operating cash flows influences analysts' coverage of firms within the same industry. They also find that earnings commonality improves analyst forecast accuracy and reduces the optimistic bias in analyst forecasts. With respect to institutional investors, Engelberg et al. (2009) find that mutual fund managers are more likely to hold portfolios of stocks that share greater commonalities in firm-level earnings. Taken together, this body of evidence indicates that greater commonality in firm fundamentals increases the value of macroeconomic and industry-level analysis to information intermediaries who actively forecast earnings performance and other economic outcomes for the firms they follow.[3]

In addition to its importance in forecasting the economic outcomes of individual firms, earnings non-commonality is linked to several other accounting phenomena. First, prior research

[3] Relatedly, Fairfield et al. (2009) provide evidence suggesting that industry-level information is closely associated with analysts' forecasts of firm-specific sales growth, while market-wide information is more closely related to forecasts of firm-specific return on equity.

documents that the degree of non-commonality in firm-level earnings is positively associated with non-commonality in stock returns, suggesting that the idiosyncratic component of firms' earnings performance (which is likely to be a product of firms' unique capabilities and internal factors) is an important determinant of stock price informativeness (Morck et al. 2000; Piotroski and Roulstone 2004; Elgers et al. 2004; Ball et al. 2009).

Moreover, recent evidence suggests that earnings (non-)commonality plays an important role in the disclosure and evaluation of firm-specific information by market participants. For instance, Gong et al. (2009) find that the degree of earnings non-commonality across related firms positively impacts the disclosure (and precision) of earnings forecasts by management. Gong et al. also find that investors react more strongly to management's earnings forecast news as the degree of earnings non-commonality increases. Kimbrough and Wang (2009) find that investors' assessment of managers' self-serving attributions in quarterly earnings press releases is dependent on the extent to which the firm's earnings performance is driven by common market and industry factors.

The preceding discussion highlights that the degree to which a firm's earnings performance share commonalities with macroeconomic and industry factors is important for forecasting and in a number of other accounting and economic contexts. However, despite this documented importance, there is surprisingly little evidence on the factors that drive the strength of these (non-)commonalities, i.e., what drives firm-level earnings to *move together or not*? We argue that such insight is particularly important because, although prior evidence generally documents the existence of industry and market influences on firm profitability, there is substantial variation in the documented strength of these influences. For instance, despite the evidence provided by Schmalensee (1985) and McGahan and Porter (1997, 2002) supporting the importance of industry factors in firm profitability, several other studies document economically small associations between industry factors and firm profitability (e.g., Ball and Brown 1967; Cubbin and Geroski 1987). Moreover, other studies indicate that the association between firm profitability and firm-specific factors greatly outweighs any association between firm profitability and industry factors (e.g., Rumelt 1991; Mauri and Michaels 1998).

2.2 Theoretical development and research questions

2.2.1 The impact of intangible investments on earnings non-commonality

While there is scant empirical evidence on the factors that drive the non-commonality of earnings across industry firms, the accounting literature (e.g., Cyert 1967; Williams 1967; Piotroski and Roulstone 2004; Elgers et al. 2004; Palepu et al. 2007) points to a firm's internal resources and its unique capabilities as likely candidates. In particular, Palepu et al. (2007) argue that intangible investments such as those related to superior customer service, brand image, R&D, and control systems focused on creativity and innovation can be a key part of a firm's competitive differentiation strategy, wherein the firm seeks to be "unique in its industry along some dimension that is highly valued by customers" (Palepu et al. 2007, chapter 2, p. 9).

The focus on intangible investments as a source of economic differentiation is consistent with the resource-based view (RBV) of the firm, which posits that a firm's endowment of resources is a significant determinant of its ability to achieve and sustain competitive advantages. Under this perspective, unique resources such as intangibles drive heterogeneity or non-commonality in economic performance among firms (Mauri and Michaels 1998). More specifically, RBV posits that intangible resources are critical to a firm's competitive strength based on the view that intangible resources are hard to acquire or develop internally (Itami 1987) and hence, are more difficult for rival firms to understand or replicate (Rumelt 1984; Nelson

1991). Given these characteristics, RBV argues that intangible resources are a key source of competitive advantage (Lippman and Rumelt 1982; Hall 1993), which in turn leads to divergences in firm profitability within the same industry.

Consistent with the above arguments, Villalonga (2004) finds that firms with high intangible resource intensity, as proxied by Tobin's Q, have more persistent earnings streams. Interestingly, Villalonga also finds that intangible intensity is positively related to the persistence of losses for poorly performing firms, suggesting that intangible assets can be a "double-edged sword" due to greater investment stickiness and/or greater appropriation of benefits by rival firms. However, Villalonga's (2004) evidence on the relation between intangible investment and earnings persistence does not provide insight into the effect of intangibles on the commonality or comovement of earnings among related firms, which is the focus of our study.

A fundamental argument of RBV is that sustainable competitive advantages stem primarily from non-appropriable resources that cannot be replicated easily by competitors (Dierickx and Cool 1989; Barney 1991; Villalonga 2004). However, an alternative perspective posited in the industrial organization literature is that the knowledge-intensity of intangibles lends them economic properties that make them uniquely susceptible to *spillovers* or appropriation by rival firms (see, e.g., Teece 1986; Dosi 1988; Lev 2001). Under this alternative view, the susceptibility of intangible investments to expropriation makes them similar to public goods from which multiple firms can benefit. As discussed by Teece (1986), the share of the profits from innovative investments often spill over to competitors and imitators, with many innovators failing to extract the full benefit of their investments. Hence, intangibles could also be a source of homogeneity or commonality in earnings among industry firms (Barney 1991).[4]

[4] Relatedly, Shiller (1989) implies that firms operating in intangible-intensive industries could exhibit a greater degree of commonality in firm performance due to imitation during R&D or technological races.

One property that makes intangibles susceptible to expropriation is that intangibles are non-rival in nature—that is, an originating firm's use of an intangible resource does not impair the potential usefulness of the same resource to those external to the originator (Romer 1990). In fact, an intangible asset often experiences increasing returns to scale. Another property is that intangible resources are only partially excludable, i.e., non-owners can rarely be precluded from enjoying some of the benefits of intangible investments (Lev 2001). This partial excludability characteristic of intangibles, and the existence of significant spillovers of benefits to non-owners, arises primarily from natural forces of diffusion that govern the spread of knowledge-based resources, which often cannot be constrained in the same manner as physical assets.[5] The forces driving the diffusion and spillover of intangible resources include employee mobility and the competitive intelligence activities of rival firms.[6, 7]

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[5]The most extensive evidence on the existence of spillovers of intangible resources can be found in the literature on R&D spillovers (see, e.g., Arrow 1962; Jaffe 1986; Levin et al. 1987; Cockburn and Griliches 1988; Davis 2001).

[6] Arrow (1962, p. 615) notes, "mobility of personnel among firms provides a way of spreading information." Consistent with this observation, Bhide (2000) finds that 71 percent of the firms included in the Inc 500 (a group of young, fast growing firms) were established by managers who exploited an innovation created by their previous employer. In addition, several studies provide evidence that managers of intangible-intensive firms view employee mobility as a competitive threat. For instance, Moen (2005) finds that high technology firms pay lower wages to their knowledge workers in apparent anticipation that such workers will expose the firm's innovative activities once they eventually leave the firm. Prior studies also document innovative firms' use of non-competition agreements to prevent spillovers due to employee mobility (e.g., Gilson 1999; Marx et al. 2009). Similarly, Erkens (2010) provides evidence that the use of stock options as a retention tool is greater for R&D-intensive firms, consistent with such firms being particularly concerned about the threat of spillover due to employee turnover.

[7] Competitive intelligence is the "methodical acquisition, analysis, and evaluation of information about competitors, both known and potential" (von Hoffman 1999, p. 3). It is predicated on the notion that firms can successfully profit from knowledge of other firms' capabilities. The competitive intelligence literature documents that firms actively attempt to learn about the innovative activities of their rivals using such sources as patent disclosures, publications, trade shows and conferences, government records, discussions with employees and sales-people of the competing firm, and reverse engineering of competitors' products (see Prescott and Bhardwaj 1995; Kahaner 1997; Lavelle 2001). Survey-based studies by Levin et al. (1987), Cockburn and Griliches (1988), and Cohen et al. (2002) corroborate that managers seek out information about their rivals' R&D efforts. Mansfield (1985) also provides survey evidence that development decisions are generally in the hands of rivals within 12 to 18 months and that detailed information regarding the nature and operation of a new product or process leaks out within about a year. Similarly, Cohen et al. (2002) report that 16% (44%) of surveyed firms in the U.S. (Japan) are aware of their rivals' R&D projects even before the development stage. The fact that typical competitive intelligence activities are oriented towards the discovery of competing firms' intangible sources of value, such as their plans, competencies, and technologies, implies that those engaged in the search for profitable information believe that the intangible resources of rival firms are particularly exploitable.

In summary, the RBV literature implies that intangible investments, because they are hard to replicate, are key determinants of heterogeneity or non-commonality in firms' earnings performance. Alternatively, the industrial organization literature posits that, because intangible assets are susceptible to expropriation, they can actually behave as public goods and, hence, are likely to be a source of commonalities in firm performance. Although these perspectives are not mutually exclusive, we seek to determine which is most descriptively valid by examining the following research question:

> RQ1: Do intangible investments affect the degree of non-commonality in firms' earnings performance?

2.2.2 The differential impact of various classes of intangible investments on earnings non-commonality.

Although the preceding discussion outlines the prevailing views on the economic properties of the broad class of intangible investments, the extent to which these properties hold is likely to vary among different classes of intangibles. The substantial literature on R&D spillovers indicates that R&D investment may behave more like a public good from which multiple firms can free ride on its benefits (see, e.g., Arrow 1962; Jaffe 1986; Levin et al. 1987; Cockburn and Griliches 1988; Davis 2001).

One way in which rivals can benefit from a firm's R&D is direct imitation (Mansfield 1985; Teece 1986; Cohen and Levinthal 1989). Cohen and Levinthal (1989) argue that firms engage in R&D efforts not only for the traditional purpose of generating their own innovations but also to develop absorptive capacity, i.e., the ability to identify, assimilate, and exploit knowledge from rival firms as well as the ability to imitate new process or product innovations. Moreover, even in the absence of direct imitation, rivals can benefit from a firm's R&D by using the technology to enhance the productivity of their own R&D efforts (Levin et al. 1987). To the extent R&D investment behaves more like a public good, it may engender relatively less non-commonality between a firm's earnings performance and that of the market and/or its industry.

In contrast to R&D investments, recognized intangible assets (with the exception of goodwill) must arise from contractual rights or must be able to be separated from the firm, which implicitly suggests the existence of enforceable property rights. As such, recognized assets may be less susceptible to expropriation and, thus, may behave less like public goods relative to R&D investments. Hence, we contend that, relative to R&D investments, recognized intangible investments will contribute to greater non-commonality in firm-level earnings.

Goodwill, while not legally protected, theoretically contains intangible benefits that are inalienable to its owner and from which other firms cannot benefit. These benefits include the expected synergies arising from past business combinations. The FASB argues that those synergies "are unique to each combination, and different combinations would produce different synergies and, hence, different values." Goodwill also captures other benefits unlikely to be expropriated by outsiders including the synergistic combination of acquired businesses' assets as well as the ability to earn monopoly profits or to impose barriers to market entry by potential competitors. Given these characteristics, we expect that goodwill will be associated with greater non-commonality (relative to R&D) in a firm's earnings performance.[8]

Based on the foregoing discussion of possible economic differences between classes of intangible assets, we examine the differential impact of various classes of intangible investment on the extent to which a firm's earnings performance is differentiated from the market and/or its industry as stated below:

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[8] We acknowledge that recognized goodwill could overstate the value of potential synergistic benefits due to the firm's possible overpayment during the acquisition process.

RQ2: Do the various classes of recognized and unrecognized intangible investments differentially affect the degree of non-commonality in firms' earnings performance?

2.2.3 The effect of property rights protection on the extent to which intangible investments contribute to earnings non-commonality.

The extent to which intangible resources are vulnerable to expropriation is not only a function of their previously discussed fundamental economic properties, but also of the strength of the property rights enforcement regime that surrounds them (Teece 1986). Intangible investments are more likely to increase the extent of earnings non-commonality if the firms making such investments are able to effectively enforce property rights such that other firms cannot readily benefit from the investments.[9] While patents and copyrights ostensibly provide property rights protection over original ideas, the effectiveness of these mechanisms in protecting intangible investments is unclear given the abundance of patent lawsuits (Lev 2001), the possibility that imitators can circumvent patents by legally inventing around them (Cohen et al. 2002), the legal hurdles to upholding patents or proving their infringement (Teece 1986; Levin et al. 1987), and the potential usefulness of patents as a basis for competitive intelligence (Horstmann et al. 1985; Levin et al. 1987; Cohen et al. 2002). Thus, it is an empirical question whether property rights protection has any impact on the extent to which intangible investments contribute to earnings non-commonality. Therefore, we examine the following research question:

RQ3: Does the strength of legal property rights protection affect the relation between intangible investment and the degree of non-commonality in firms' earnings performance?

3. Variable measurement and empirical specifications

[9] This argument is also consistent with Matolcsy and Watts (2008) who find that appropriability conditions surrounding the firm's intangible investments have a significant impact on the firm's future earnings growth and, in turn, its market value of equity.

3.1 Measurement of earnings non-commonality

We estimate the idiosyncratic component of a firm's earnings performance (i.e., earnings non-commonality) based on the methodology outlined in prior studies (e.g., Morck et al. 2000; Durnev et al. 2004; Piostroki and Roulstone 2004; Elgers et al. 2004). This methodology estimates the portion of firm-level earnings that cannot be explained by market-level or industry-level earnings.[10] Specifically, for each quarter, we estimate the following firm-specific regression model over the 20 calendar quarters preceding and including quarter t (requiring a minimum of 10 quarterly observations):

$$ROA_{i,t} = \alpha_0 + \alpha_1 MKTROA_{i,t} + \alpha_2 INDROA_{i,t} + \varepsilon_{i,t} \tag{1}$$

where:

$ROA_{i,t}$ = return on assets for firm i during calendar quarter t, measured as reported income before extraordinary items (Compustat data item IBQ) plus quarterly R&D expense (data item XRDQ) less the estimated quarterly R&D amortization expense, scaled by the sum of total recognized assets (*ASSETS*, data item ATQ) and estimated R&D capital (*RDCAPITAL*) as of the beginning of calendar quarter t;

$MKTROA_{i,t}$ = the weighted average ROA (adjusted for R&D capitalization) for all Compustat firms excluding those in the same two-digit SIC code as firm i during calendar quarter t, measured as the sum of adjusted income before extraordinary items for all Compustat firms excluding those in the same two-digit SIC code as firm i scaled by the sum of total recognized assets and estimated R&D capital as of the beginning of calendar quarter t for all Compustat firms excluding those in the same two-digit SIC code as firm i;

$INDROA_{i,t}$ = the weighted average ROA (adjusted for R&D capitalization) for all Compustat firms excluding firm i in the same two-digit SIC code, measured as the sum of adjusted income before extraordinary items for all Compustat firms in the same two-digit SIC code excluding firm i scaled by the sum of total recognized assets and estimated R&D capital as of the beginning of calendar quarter t for all Compustat firms in the same two-digit SIC code excluding firm i.

Consistent with prior research, we use return on assets (ROA)—modified for R&D capitalization—as our measure of firm-level earnings. Following Kothari et al. (2002), we

[10] This methodology is similar to that used in prior studies to estimate comovement or non-commonalities in stock returns (see, e.g., Morck et al. 2000: Durnev et al. 2004; Piostroki and Roulstone 2004). We also use this methodology to construct our measure of stock return non-commonality as outlined in Section 5.2.1.

estimate R&D capital (*RDCAPITAL*) each year as the unamortized cost of R&D investment using current and past R&D expenditures amortized at an annual rate of 20% (i.e., assuming a five-year useful life and straight-line depreciation).[11] In calculating *ROA*, we add back quarterly R&D expense to quarterly earnings (consistent with Kothari et al. 2002) and then subtract the estimated quarterly R&D amortization expense. Next, we adjust beginning-of-quarter assets (*ASSETS*) for the implicit capitalization of R&D by adding the estimated amount of R&D capital as of the beginning of quarter *t*. We calculate R&D capital as of the beginning of each quarter by updating the prior year's R&D capital estimate for subsequent quarterly R&D expenditures[12] and quarterly R&D amortization.[13]

The weighted average *ROA* for the market (*MKTROA*) is calculated using all firm-quarters with available data in the Compustat database and beginning of quarter assets as the weight. Similarly, the weighted average *ROA* for each industry (*INDROA*) is calculated using all other firms within the same two-digit SIC code as firm *i*.[14] We then define earnings non-commonality as the unexplained portion of the firm's *ROA* (*UNEXPLAINED*), i.e., 1 minus the R^2 from each firm-specific regression of Equation 1. Lastly, following prior research (Piostroki and Roulstone 2004), we create an unbounded continuous variable for each firm-quarter using the log transformation of *UNEXPLAINED* as defined below:

[11] This treatment is also consistent with Lev and Sougiannis (1996) who report that the useful life of R&D capital is, on average, five to seven years for most industries.
[12] We obtain quarterly R&D expenditures from the quarterly Compustat file, when available. In cases where actual quarterly R&D expenditures are not available due to the sparseness of quarterly R&D data in Compustat, we estimate the quarterly expenditures by assuming that the annual R&D expenditures as reported in the annual Compustat file occurs evenly across all four quarters within the fiscal year. That is, for each quarter, we calculate quarterly R&D expenditures as annual R&D expenditures divided by four.
[13] Under the assumption that the implicit amortization of R&D expenditures under a capitalization regime occurs evenly throughout the year, we estimate quarterly R&D amortization as the estimate of annual amortization (based on the 20% amortization rate applied to historical R&D expenditures) divided by four.
[14] Our results and inferences are unchanged when we use four-digit SIC codes to classify industries.

$$NONCOMMON_{i,t} = log\left(\frac{UNEXPLAINED_{i,t}}{1-UNEXPLAINED_{i,t}}\right) \quad (2)$$

Note that higher values of *NONCOMMON* indicate those quarters in which the firm's *ROA* varies strongly with firm-specific factors as opposed to market-wide and industry-level factors. Appendix 1 summarizes the measurement of our earnings non-commonality and all of the variables discussed below.[15]

3.2 Measurement of firm-level intangible resources

To capture the firm's total investment in intangible resources (*INTANGIBLES*), we aggregate for each quarter the firm's investments in separable recognized intangible assets (except goodwill, *SEPARABLE*), goodwill (*GOODWILL*), and R&D capital (*RDCAPITAL*).[16] *SEPARABLE* and *GOODWILL* capture those intangible investments that are accorded accounting recognition. Separable intangibles (excluding goodwill) typically include patent costs, copyrights, licenses, contract rights, trademarks, and trade names (data item INTANQ). Goodwill captures the expected synergistic benefits arising from past business combinations (data item GDWLQ). R&D capital is a specific unrecognized intangible investment that has been examined by several accounting studies (e.g., Barth and Kasznik 1999; Barth et al. 2001; Lev and Sougiannis 1996; Kothari et al. 2002).

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[15] Our earnings non-commonality measure is qualitatively similar to that used in De Franco et al. (2009) and Gong et al. (2009). De Franco et al. (2009) and Gong et al. (2009) construct their measure using the average pair-wise correlation between a firm's earnings and the earnings of each of its industry peers. However, we choose not to use this methodology because it excludes explicit controls for the systematic correlation between firm-level earnings and the earnings across all firms in the market as documented in prior research (e.g., Ball and Brown 1967; Magee 1974). Finally, we note that prior studies find no difference in their results when (non-)commonality measures are constructed based on pair-wise correlations of individual firm performance as opposed to correlations with average industry performance (see Morck et al. 2000 and Gong et al. 2009).

[16] We do not examine advertising as a separate class of intangibles for the following reasons: First, the data for advertising expenditures is even sparser in the quarterly Compustat file. Second, prior studies report that the immediate and future benefits of advertising are short-lived, lasting for only a few months or one year (Peles 1970; Lev and Sougiannis 1996).

For each quarter t, we compute the firm's average intangible asset intensity (*INTANGIBLEINTENSITY*) as the aggregate level of intangibles (*INTANGIBLES*) scaled by the sum of total recognized assets (*ASSETS*) and R&D capital (*RDCAPITAL*), and then taking the average over the 20-quarter period used to estimate our earnings non-commonality measures in Equation 1. That is:

$$INTANGIBLEINTENSITY_{i,t} = \frac{\sum_{q=-19}^{0}\left(\frac{INTANGIBLES_{i,t+q}}{ASSETS_{i,t+q} + RDCAPITAL_{i,t+q}}\right)}{N} \qquad (3)$$

where *INTANGIBLES* equals (*SEPARABLE* + *GOODWILL* + *RDCAPITAL*), and N is the number of non-missing observations over the 20-quarter period. We calculate an average intensity measure over the same 20-quarter period used to estimate Equation 1 to ensure consistency in the measurement period of all of our regression variables.

As described in the Appendix, we use analogous procedures to calculate the average quarterly intensity for the separate components of recognized and unrecognized intangibles (i.e. *SEPARABLEINTENSITY*, *GOODWILLINTENSITY*, and *RDINTENSITY*). In addition, we include the average quarterly market-to-book ratio (*MB*) in our regressions in order to provide insight on the impact of unrecognized intangibles not reflected in our *INTANGIBLEINTENSITY* measure. The market-to-book ratio uses the market's valuation of the firm's wealth creation as a basis for inferring the value of intangible resources not accorded accounting recognition as well as the value of R&D investments that are omitted from our estimate of the firm's R&D capital (e.g., write-offs of purchased R&D).[17]

3.3 Empirical specifications

[17] Similar to the closely related Tobin's Q measure, the market-to-book ratio is not a perfect proxy for unrecorded intangibles to the extent that it reflects the market's upward revaluations of recorded tangible and intangible assets as well as the effect of accounting conservatism on the net book values of recorded assets.

To investigate our first research question (RQ1), we estimate the effect of intangible resources on firm-level earnings non-commonality using the following regression model:

$$\begin{aligned} NONCOMMON_{i,t} = {} & \beta_0 + \beta_1 log(1 + INTANGIBLEINTENSITY_{i,t}) + \beta_2 log(MB_{i,t}) + \\ & \beta_3 log(MVE_{i,t}) + \beta_4 MKTSHARE_{i,t} + \beta_5 STDROA_{i,t} + \beta_6 log(1 + DIVERS_{i,t}) + \\ & \beta_7 log(1 + HERF_{i,t}) + \beta_8 log(1 + LEVERAGE_{i,t}) + \beta_9 REG_{i,t} + \\ & \beta_{10} log(NIND_{i,t}) + \varepsilon_{i,t} \end{aligned} \tag{4}$$

We describe the measurement of each of the control variables in the Appendix. With the exception of *REG*, all of our regression variables are averaged over the estimation period used to calculate the earnings non-commonality measures from Equation 1 (i.e., *UNEXPLAINED* and *NONCOMMON*). In addition, we log transform the values of *INTANGIBLEINTENSITY* and several of our control variables to mitigate the effect of skewness in the distributions of the respective variables.

The specification in Equation 4 estimates the association between earnings non-commonality (*NONCOMMON*) and the firm's average intangible intensity (*INTANGIBLEINTENSITY*). As previously discussed, if intangible resources are indeed a source of economic differentiation among industry firms, then we expect a positive association between *INTANGIBLEINTENSITY* and *NONCOMMON*. On the other hand, if intangible resources operate more as a public good due to expropriation or spillover to rival firms, then we could find a negative association between *INTANGIBLEINTENSITY* and *NONCOMMON*.

Consistent with prior research (e.g., Morck et al. 2000; Durnev et al. 2003, 2004; Piostroski and Roulstone 2004), we control for several other determinants of firm-level variation in economic fundamentals. These control variables primarily capture the underlying economics of the firm and its industry. Specifically, we control for firm size (*MVE*) and market share (*MKTSHARE*) since the resources and business activities of large firms as well as market leaders may exhibit greater heterogeneity, which in turn suggests that the profitability of large firms or firms with greater market share might move independently of industry- and market-wide factors (Barney 1991; Morck et al. 2000). Alternatively, the business activities of large, market dominant firms often induce rivals to engage in similar strategies, which in turn could lead to greater commonality in firms' earnings performance. Given these conflicting arguments, we offer no directional predictions for the effects of *MVE* and *MKTSHARE* on *NONCOMMON*.

The standard deviation of ROA (*STDROA*) captures the volatility in firms' earnings performance. As argued by Piotroski and Roulstone (2004), firms with higher earnings volatility should exhibit a greater degree of earnings non-commonality, suggesting a positive association between *NONCOMMON* and *STDROA*. We control for the diversity of the firm's operations (*DIVERS*) since the consolidated profitability of diversified firms is less sensitive to macroeconomic shifts or shifts in the earnings performance of its primary industry affiliation. However, the profitability of the various business segments of diversified firms may produce off-setting idiosyncratic results, which in turn could increase the comovement of the firm's earnings performance with that of its industry and the overall market. Given these arguments, we refrain from making a directional prediction of the association between *NONCOMMON* and *DIVERS*. We also control for the level of industry concentration (*HERF*) because the economic fundamentals of firms operating in a highly concentrated industry could be strongly correlated (Morck et al. 2000), thereby resulting in greater earnings comovement. We predict a negative association between *NONCOMMON* and *HERF*.

Prior studies indicate that intangible-intensive firms are considerably less leveraged than other firms, presumably as a consequence of higher agency costs and creditors' preference to use tangible assets to secure loans (see Bradley et al.1984; Long and Malitz 1985; Hall 2002).[18] Furthermore, existing theory and evidence indicate that higher financial leverage is associated with greater earnings volatility (e.g., Beaver et al. 1970; Kothari et al. 2002), thereby resulting in greater non-commonality in firm-level earnings (Piotroski and Roulstone 2004). Given these arguments, we control for firm leverage (*LEVERAGE*) as a possible correlated factor of intangible intensity and earnings non-commonality.

Lastly, we control for those firms that operate in a regulated industry (*REG*) as well as the average number of firms within the industry (*NIND*). Firms operating in a regulated industry are subject to common constraints on their operations and thus, their earnings should respond similarly to changes in industry regulations and conditions (Piostroki and Roulstone 2004). We therefore expect a negative association between *NONCOMMON* and *REG*. We also include the average number of same-industry firms (*NIND*) to control for spurious correlations between our earnings non-commonality measure and the size of the industry.[19] Moreover, larger industries may be more mature, contain more homogenous firms, and as such, may exhibit less earnings non-commonality (Durnev et al. 2004).

Our second research question (RQ2) addresses the differential impact of various classes of intangible investments on the degree of earnings non-commonality. To examine this issue, we estimate the following regression model, which decomposes *INTANGIBLEINTENSITY* into its separate classes of recognized and unrecognized intangible intensity: the average intensity of separable recognized intangibles (*SEPARABLEINTENSITY*), average goodwill intensity (*GOODWILLINTENSITY*), and average R&D intensity (*RDINTENSITY*).

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[18] Bradley et al. (1984) also posit that intangible intensive firms are less likely to issue debt since the full expensing of unrecognized intangible investments such as R&D serves as a non-debt tax shield, thereby decreasing the tax advantage of debt financing.

[19] Given the Law of Large Numbers, measures of earnings non-commonality will by default decrease with the number of firms within the industry (see Morck et al. 2000 and Durnev et al. 2003 for further details).

$$
\begin{aligned}
NONCOMMON_{i,t} = {} & \delta_0 + \delta_1 log(1 + SEPARABLEINTENSITY) + \\
& \delta_2 log(1 + GOODWILLINTENSITY_{i,t}) + \delta_3 log(1 + RDINTENSITY_{i,t}) + \\
& \delta_4 log(MB_{i,t}) + \delta_5 log(MVE_{i,t}) + \delta_6 MKTSHARE_{i,t} + \delta_7 STDROA_{i,t} + \\
& \delta_8 log(1 + DIVERS_{i,t}) + \delta_9 log(1 + HERF_{i,t}) + \delta_{10} log(LEVERAGE) + \\
& \delta_{11} REG_{i,t} + \delta_{12} log(NIND_{i,t}) + \varepsilon_{i,t} \qquad (5)
\end{aligned}
$$

Our next research question (RQ3) investigates the incremental effect of legal property rights protection on the association between intangible investments and earnings non-commonality. We use the industry-level survey results of Cohen et al. (2000) to measure the strength and effectiveness of property rights mechanisms within each industry. The survey results reported in Cohen et al. (2000) are based on the 1994 Carnegie Mellon Survey on Industrial R&D in the U.S. manufacturing sector (SIC 20 - 39). The Carnegie Mellon Survey was limited to manufacturing firms and targeted R&D managers who were asked to report on the effectiveness of several mechanisms in protecting the firm's product and process innovations during the 1991 to 1993 period. While the survey data does not overlap with our entire sample period, prior research argues that industry appropriability conditions are relatively stable over time (Cohen and Levin 1989). Moreover, the results reported in Cohen et al. (2000) confirm the earlier survey results of Mansfield (1986) and Levin et al. (1987), suggesting that industry appropriability conditions are indeed stable over time.[20]

Consistent with prior research (e.g., Erkens 2010), we first average the mean effectiveness scores reported in Cohen et al. (2000) for R&D product and process innovations for each of the following two mechanisms: (1) patents and (2) other legal protections. For each two-digit SIC code, we sum the average effectiveness scores for patents and other legal protections to

[20] The 1994 Carnegie Mellon Survey builds and improves on the 1983 Yale Survey of industry appropriability conditions conducted by Levin et al. (1987). We do not use the 1983 Yale Survey results given the improvements in the question wording, response scales, and sampling strategy of the 1994 Carnegie Mellon Survey. In a limited comparison of the 1983 and 1994 survey results, Cohen et al. (2000) find that the effectiveness of patents for product innovations have increased only slightly for large firms, while the effectiveness of patents for process innovations remains stable across all firms.

create a comprehensive measure of the effectiveness of property rights protection at the industry level.[21] This measurement procedure is conducted only for firms operating in the manufacturing industry since the Carnegie Mellon Survey is limited to manufacturing firms. We then create a binary variable, denoted *LEGALRIGHTS*, which equals "1" if the firm operates in a manufacturing industry with an aggregate effectiveness score that is at or above the median score across all the manufacturing industries in our sample; and "0" otherwise.

To examine the incremental effect of property rights protection, we re-estimate Equation 5 after including the main and interaction effects of *LEGALRIGHTS* on the association between *NONCOMMON* and *RDINTENSITY*. The regression model is as follows:

$$\begin{aligned} NONCOMMON_{i,t} &= \gamma_0 + \gamma_1 log(1 + SEPARABLEINTENSITY_{i,t}) + \\ &\gamma_2 log(1 + GOODWILLINTENSITY_{i,t}) + \gamma_3 log(1 + RDINTENSITY_{i,t}) + \\ &\gamma_4 \left[log(1 + RDINTENSITY_{i,t}) \times LEGALRIGHTS_{i,t}\right] + \gamma_5 LEGALRIGHTS_{i,t} + \gamma_6 log(MB_{i,t}) + \\ &\gamma_7 log(MVE_{i,t}) + \gamma_8 MKTSHARE_{i,t} + \gamma_9 STDROA_{i,t} + \gamma_{10} log(1 + DIVERS_{i,t}) + \\ &\gamma_{11} log(1 + HERF_{i,t}) + \gamma_{12} log(1 + LEVERAGE) + \gamma_{13} log(NIND_{i,t}) + \varepsilon_{i,t} \qquad (6) \end{aligned}$$

Because the Carnegie Mellon Survey relates only to the appropriability conditions surrounding firms' R&D investments, we do not interact *LEGALRIGHTS* with *SEPARABLEINTENSITY* or *GOODWILLINTENSITY*. Also, we exclude the indicator variable, *REG*, since the Carnegie Mellon Survey results apply only to firms operating in the manufacturing industry.

4. Sample selection and descriptive evidence

4.1 Sample selection

Our initial sample consists of all firm-quarters in the CRSP/COMPUSTAT merged database for the years spanning the 1980 to 2006 period. We first eliminate all firm-quarters with missing information for calculating our regression variables. Further, we eliminate firms with a

[21] The data in Cohen et al. (2000) are reported at the industry level using ISIC codes. We thank David Erkens for providing information to re-classify the ISIC codes into the appropriate SIC codes.

non-classifiable industry code (SIC 99). We require each firm-quarter to have non-missing data for at least 10 calendar quarters preceding the current quarter *t*. To mitigate the potential effects of serial correlation arising from the use of overlapping rolling windows to estimate the earnings non-commonality measures, we conduct our empirical analyses using data only for the fourth calendar quarter of each firm-year.[22] These data restrictions result in a final full sample of 119,436 firm-years for 13,685 unique firms.[23] We use the full sample to assess our first and second research questions (RQ1 and RQ2). For our third research question (RQ3), we use a reduced sample of 51,401 firm-years because data for the calculation of the industry-level property rights protection measure (*LEGALRIGHTS*) are available only for the manufacturing industry (SIC 20 - 39).

4.2 Descriptive evidence

Table 1 provides information on the composition of the full sample by industry. From Table 1, we note that the most represented industries are Business Services (SIC 73), which comprises 9.7% of the sample; Electronic and Other Electrical Equipment (SIC 36), which comprises 7.9% of the sample; and Chemicals and Allied Products (SIC 28), and Industrial and Commercial Machinery (SIC 35), which both comprise about 6.5% of the sample. This sample distribution is comparable to the industry distribution of all firms covered by the CRSP/Compustat database.

[22] As discussed in Section 5.1.1, we further correct for serial correlation using the two-way clustering approach suggested by Petersen (2009). A similar clustering approach is used in prior research on stock return comovement (see Jin and Myers 2006). Also, in robustness tests (see Section 5.2.3), our inferences are unchanged when we conduct our empirical tests using non-overlapping subsamples where each firm-year observation is five years (i.e., 20 calendar quarters) apart.
[23] We find similar evidence after eliminating those observations with a negative book value of equity as well as observations with a market value of equity that is less than book value. These additional data restrictions attempt to control for firms with possible asset impairments.

Table 2 provides descriptive statistics for our regression variables. The mean (median) of *UNEXPLAINED* from the estimations of Equation 1 is 0.760 (0.807), indicating a relatively weak association between firm-level earnings and the value-weighted indices of market- and industry-wide earnings.[24] However, we note that the standard deviation of *UNEXPLAINED* (0.194) is considerably large compared to the median value. This statistic indicates that our sample exhibits considerable cross-sectional variation in the degree of earnings non-commonality at the firm level. Similar conclusions can be drawn from the summary statistics for *NONCOMMON*, which is the log transformation of *UNEXPLAINED*. Our summary statistics for the reduced sample to be used in supplemental tests of returns non-commonality are similar. Specifically, we find that the mean (median) of *UNEXPLAINED_RET* is 0.785 (0.824), indicating that a significant portion of the variation in stock returns is not explained by industry or market returns.

The mean (median) of *INTANGIBLEINTENSITY* is 0.125 (0.052), indicating that, on average, intangible assets comprise about 13% of the total value of firm's recognized and unrecognized assets. In addition, the descriptive statistics for the separate classes of intangibles suggest that R&D capital accounts for the majority of firms' total intangible assets. Specifically, the mean value of *RDINTENSITY* is 0.071 compared to the mean values of 0.013 and 0.041 for *SEPARABLEINTENSITY* and *GOODWILLINTENSITY*, respectively. These differences in means are significant at the 1% level based on *t*-tests and Wilcoxon rank sum tests.

With respect to our control variables, we find that the mean (median) of the average market value of equity (*MVE*) is $1.2 billion ($87.4 million), indicating that our sample captures

[24] This evidence is consistent with Gong et al. (2009) who report that, on average, 88% of firm-level earnings are not explained by market- and industry-wide factors. Similarly, Kimbrough and Wang (2009) report a mean earnings non-commonality measure of 71% for a smaller sample of firms.

a substantial portion of the U.S. capital market.[25] We further note that our sample industries are relatively large as indicated by the mean (median) of 256 (203) for the average number of same-industry firms (*NIND*). We also observe that about 5.6% of our sample firms operate in a regulated industry (*REG*). The distributions of the rest of our control variables are consistent with prior research, though we do not discuss them for brevity.

Table 3 presents pairwise correlation coefficients for our regression variables. Pearson (Spearman) coefficients are presented above (below) the diagonal. We find significantly positive correlations between *NONCOMMON* and *INTANGIBLEINTENSITY*, thus providing preliminary evidence that intangible investments contribute to the idiosyncratic component of firms' earnings performance. The Spearman correlations for the separate classes of intangibles indicate that *NONCOMMON* is positively associated with *SEPARABLEINTENSITY* and *RDINTENSITY*, but not significantly associated with *GOODWILLINTENSITY*. Moreover, the positive correlation between *NONCOMMON* and the market-to-book ratio (*MB*) suggest that other unrecognized intangibles may have a positive incremental effect on earnings non-commonality. Finally, we note that the signs of the correlations between *NONCOMMON* and our control variables are consistent with the predictions discussed previously in Section 3.2.

5. Empirical results and robustness tests

5.1 Empirical results

5.1.1 Do intangible investments affect the degree of earnings non-commonality (RQ1)?

Columns 1 to 3 of Table 4 present the estimated results for Equation 4. To control for heteroskedasticity and unobserved within-firm and time-series correlation patterns, we base our inferences on standard errors clustered by firm and calendar year (Petersen 2009). This two-way

[25] During our sample period, the mean (median) composite value of the NYSE, AMEX, and NASDAQ ranges from $1.4 trillion in 1980 to $19.5 trillion in 2006.

clustering approach also corrects for serial correlation that may arise from the use of overlapping rolling windows to estimate the earnings non-commonality measure (*NONCOMMON*). As noted earlier, we log transform several of the regression variables to control for skewness in the data distributions.

The estimated coefficient on *INTANGIBLEINTENSITY* is significantly positive (β_1 = 0.402, $p < 0.001$), suggesting that investment in intangible assets has a positive impact on the degree of earnings non-commonality. We also find a significantly positive association between *NONCOMMON* and the market-to-book ratio (*MB*; $\beta_2 = 0.052$, $p < 0.001$), indicating that other unrecognized intangible assets (i.e., those intangibles not captured by our *INTANGIBLEINTENSITY* measure) have a positive incremental effect on the extent of earnings non-commonality. These results are consistent with the resource-based view, which argues that intangible investments are important drivers of economic differentiation among firms. Thus, it appears that the resource-based view of intangible resources—rather than the public good view—is most descriptive of our sample.

With respect to our control variables, we find that the earnings performance of large firms exhibits greater commonality with market- and industry-wide factors, as indicated by the significantly negative coefficient on *MVE*. This result is consistent with the argument that large firms often act as market leaders and may induce rival firms to engage in similar business strategies, thereby resulting in greater comovement in the earnings of large firms. The significantly negative coefficient on *DIVERS* and *HERF* suggests that less diversified firms and firms operating in highly concentrated industries tend to have a lower degree of earnings non-commonality. Consistent with our predictions, the significantly positive coefficients on *STDROA* indicate that firms with more volatile earnings have less comovement in their earnings streams.

Contrary to expectations, we find that firms operating in regulated industries (*REG*) tend to have less earnings commonality, as evidenced by the positive association between *NONCOMMON* and *REG*.[26]

Taken together, the results in Table 4 suggest that investment in intangible resources is an important factor that drives the extent of non-commonality in firm-level earnings, consistent with the resource-based view of intangibles. Moreover, the estimated signs of our control variables are largely consistent with prior research (e.g., Morck et al. 2000; Piostroski and Roulstone 2004) and, thus, further validate our results.

5.1.2 Do the various classes of recognized and unrecognized intangibles investments differentially affect the degree of earnings non-commonality (RQ2)?

The results for RQ1 suggest that intangible investments are positively associated with the idiosyncratic component of firm profitability. Our next set of analyses extends this evidence by examining the differential impact of various classes of recognized and unrecognized intangibles on earnings non-commonality.

Columns 4 to 6 of Table 4 present the regression results for Equation 5, which estimates the associations between *NONCOMMON* and the average asset intensity level for the following classes of intangibles: separable recognized intangibles (*SEPARABLEINTENSITY*), goodwill (*GOODWILLINTENSITY*), and R&D capital (*RDINTENSITY*). We again base our inferences on robust standard errors corrected for heteroskedasticity and two-way clustering by firm and calendar year (Petersen 2009). The estimated coefficients for *SEPARABLEINTENSITY* (δ_1 = 0.803; p = 0.001), *GOODWILLINTENSITY* (δ_2 = 0.325; p = 0.040), and *RDINTENSITY* (δ_3 =

[26] In supplemental tests (see Table 6), we find a significantly negative association between *REG* and non-commonalities in stock returns, consistent with prior studies. As discussed in Section 5.2.1., this differential result likely reflects differences in the time horizons captured by earnings- versus returns-based non-commonality measures.

0.309; p = 0.009) collectively suggest that both recognized and unrecognized intangibles contribute significantly to earnings non-commonality on average. Notably, we find that the estimated coefficient for *SEPARABLEINTENSITY* is significantly higher than each of the estimated coefficients for *GOODWILLINTENSITY* and *RDINTENSITY* (*F*-tests of these differences in the coefficients are significant at less than the 5% level). This finding suggests that, relative to goodwill and R&D capital, separable recognized intangibles have a greater impact on earnings non-commonality, consistent with the conjecture that intangible assets arising from contractual or legal property rights are more excludable and thus, less susceptible to expropriation or spillover to rivals. In summary, the results in Table 4 indicate that the extent to which various classes of intangible investments engender economic differentiation depends on their underlying properties.

5.1.3 Do legal property rights protection affect the relation between intangible investment and earnings non-commonality (RQ3)?

In this section, we provide further evidence of the incremental effect of enforceable property rights on the association between intangible investments and earnings non-commonality. We investigate this issue using a comprehensive industry-level measure (*LEGALRIGHTS*) of the effectiveness of legal property protection mechanisms for R&D investments as reported in Cohen et al. (2000). As discussed in Section 3.3, the *LEGALRIGHTS* measure applies only to R&D investments and is constructed based on survey data from firms operating in the manufacturing industry. Therefore, we conduct our empirical tests using a subsample of firms (51,401 firm-years) operating in the manufacturing industry (SIC 20 - 39).

Table 5 presents the regression results for Equation 6.[27] Our results indicate that the interaction of *RDINTENSITY* with *LEGALRIGHTS* is significantly positive (γ_4 = 0.493; p = 0.029), suggesting a greater positive effect of *RDINTENSITY* on *NONCOMMON* for those industries with strong legal property rights mechanisms for R&D innovations. This result supports the conjecture that firms' ability to appropriate the benefits of their intangible investments significantly influences the extent to which intangible investments contribute to economic differentiation as reflected in the degree of earnings non-commonality.

5.2 Extensions and robustness tests

5.2.1 Intangible investment and non-commonality in stock returns

We focus on earnings non-commonality in our primary tests because this measure most closely captures correlation in firm fundamentals, which is our construct of interest. By contrast, non-commonality in stock returns captures not only correlation in firm fundamentals but also factors related to a firm's information and trading environments. Nevertheless, we extend our analysis to non-commonality in stock returns because this measure potentially yields valuable insights. Specifically, given that stock returns presumably reflect economically important phenomena, tests using non-commonality in stock returns provide a useful gauge of the economic significance of our earnings-based findings. In addition, because stock returns reflect not only realized economic performance but revisions in anticipated future performance, tests using non-commonality in stock returns provide greater insight on the anticipated long-run impact of intangible investment than our earnings-based measure, which only reflects correlations in short-run economic performance. Finally, while earnings-based measures of non-

[27] Recall that we do not interact *LEGALRIGHTS* with *SEPARABLEINTENSITY* nor *GOODWILLINTENSITY* since the survey data relates only to the appropriability conditions surrounding R&D investments.

commonality may partly reflect differences in accounting treatment of economic events across firms (De Franco et al. 2009; Durnev et al. 2003; Elgers et al. 2004), stock return-based measures have no such limitation.

As described in the Appendix, we construct our stock return non-commonality measure (*NONCOMMON_RET*) in a manner analogous to earnings non-commonality (*NONCOMMON*). We re-estimate our results using extended versions of Equations 4 to 6, where we replace the dependent variable *NONCOMMON* with *NONCOMMON_RET* and include several variables suggested by Piotroski and Roulstone (2004). These additional variables include *NONCOMMON* (which corresponds with the degree of correlation in underlying firm fundamentals) as well as several variables related to the information- and trading-related activities of financial analysts and institutional investors including: forecast revision frequency (*NREV*), share turnover by institutional investors ($\Delta INST$), and net share purchase activity by insiders (*TRADES*). We describe the measurement of these variables in the Appendix. Due to additional data restrictions, our test sample reduces to 41,312 for the estimation of the expanded versions of Equations 4 and 5, and to 19,343 for the estimation of the expanded version of Equation 6.

The results presented in Table 6 are largely consistent with our earnings non-commonality tests. That is, we find that total intangible intensity is positively related to non-commonality in returns ($p = 0.034$) and that goodwill and separable intangible assets individually are also positively related to non-commonality in stock returns ($p < 0.01$).

In contrast to the earnings-based tests, however, we find that R&D is negatively related to returns non-commonality. This result is consistent with the extensive literature on R&D spillovers. The differing effects of R&D for the earnings-based versus the returns-based measures of non-commonality likely reflect differences in the time horizons captured by the two measures. While our earnings based-measure captures associations between a firm's realized performance and the realized performance of the market and the firm's industry over quarterly intervals, the returns-based measure not only captures associations between realized performance over short horizons but also associations between anticipated long-run performance. Thus, while our earnings-based measure suggests that R&D allows firms to differentiate themselves economically in the short-run, our returns-based measure suggests that the market anticipates that the dominant effect of R&D in the long run will be to generate economic commonalities.[28]

Lastly, Table 7 presents the re-estimated results for Equation 6. Consistent with the analogous earnings-based tests presented in Table 5, the positive coefficient on the interaction between *RDINTENSITY* and *LEGAL RIGHTS* ($p = 0.013$) indicates that the existence of effective legal property rights is instrumental in the extent to which R&D investment contributes to non-commonalities in fundamental performance.

5.2.2 Earnings forecasting and intangibles-driven non-commonality in earnings

An implication of our findings is that intangible investment affects the relative importance of market-wide and industry-wide information when forecasting an individual firm's earnings. We formally examine this implication by testing the effect of intangible investment on the accuracy improvements generated by the market- and industry-based profitability forecast models set forth in Fairfield et al. (2009). Their basic profitability forecast model regresses return on net operating assets (*RNOA*) on: (1) lagged *RNOA*, (2) an interaction between *RNOA* and a dummy variable corresponding to *RNOA* that is below the median, and (3) predicted sales growth from a first-order autoregressive sales growth forecast model.

[28] Survey evidence provided by Mansfield (1985) that development decisions are generally in the hands of rivals within 12 to 18 months and that detailed information regarding the nature and operation of a new product or process leaks out within a year lends plausibility to this interpretation.

Consistent with Fairfield et al. (2009), for each prediction year, we estimate the profitability forecast model on a relevant sample of firms for the 10 year period preceding the prediction year and apply the resulting coefficients on prediction year values in order to generate one-year ahead profitability forecasts. The relevant sample of firms for the market-based model consists of all Compustat firms with the necessary data while the relevant sample of firms for the industry-based model consists of all Compustat firms in the same industry (i.e. two-digit SIC code) as the firm for which a forecast is being generated. Consistent with Fairfield et al. (2009), we assess the relative forecasting performance of the market-based model against a naive random-walk expectation model and the relative performance of the industry-based model against the market-based model.

Panel A of Table 8 presents the average forecast accuracy improvements generated by the market-wide and industry-specific models for 87,865 firm-years from 1980 to 2006 with the necessary data. Similar to Fairfield et al. (2009), we document significant forecast accuracy improvements from using the market-wide model over a random walk expectation ($p < 0.001$) but no significant forecast accuracy improvements from using the industry-based model over the market-wide model ($p = 0.727$). Fairfield et al. (2009) attribute the latter finding to unspecified heterogeneity among firms in the same industry, which hinders the ability of the industry-based models to improve upon market-based models. Our analysis sheds light on whether intangible investment is a source of this heterogeneity.

Panel B of Table 8 presents the results of regressing individual firm-year forecast accuracy improvements for the market model (*IMPROVE_MKT*) against firm-year measures of intangible intensity and its components. While we fail to find a significant relation between total intangible intensity and forecast accuracy improvements, we find that both separable recognized assets and goodwill reduce the improvements generated by the market-wide model (p = 0.061 and 0.002, respectively). This finding indicates that economy-wide information is relatively less important in forecasting the profitability of firms that possess intangibles that lead to economic differentiation. By contrast, we find that R&D intensity increases the forecast improvements generated by the market-wide model (p = 0.040), suggesting that the market-wide model is better specified for R&D firms due to the greater commonality engendered by R&D investment (as reflected in the previously discussed return non-commonality tests).

Panel C of Table 8 presents the results of regressing individual firm-year forecast accuracy improvements for the industry-specific model (*IMPROVE_IND*) against firm-year measures of intangible intensity and its components. We find a significantly positive relation between total intangible intensity and forecast accuracy improvements (p = 0.065). This relation appears to be driven by the positive impact of R&D investment (p < 0.001) that offsets the negative impact of goodwill investment (p < 0.001). These findings reinforce the notion that the commonalities generated by R&D (the heterogeneity associated with goodwill) increase (decrease) the importance of industry information in firm-specific profitability forecasts.

5.2.3 Additional robustness tests

We explore the robustness of our results to several additional, untabulated procedures. First, to control for the possible effect of accounting method differences on our earnings non-commonality measure (*NONCOMMON*), we recalculate *NONCOMMON* using ROA based on earnings before interest, taxes, depreciation, and amortization (appropriately adjusted for R&D amortization and capitalization) based on Durnev et al.'s (2003) insight that interest, taxes, depreciation, and amortization are the components of earnings that are most vulnerable to differences in accounting practices. Second, we re-estimate all our regressions after excluding all observations with zero values for average intangible intensity. Finally, as an additional step to address potential serial correlation due to the use of overlapping windows in the estimation of *NONCOMMON*, we replicate our empirical tests using subsamples of firm-year observations with completely non-overlapping data.[29] Our inferences are robust to these additional procedures.

6. Conclusion

In this study, we examine the effect of intangible investment on the extent to which a firm's earnings performance is driven by firm-specific factors, as measured by the degree of earnings non-commonality — an important determinant of several accounting and market phenomena documented in prior research. For a sample of U.S. firms over the 1980 to 2006 period, we find a positive relation between a firm's intangible asset intensity and the non-commonality of its earnings performance. Our results are consistent with the resource-based view of intangible investments, which posits that intangible investments allow firms to differentiate themselves from their rivals.

We find that separable recognized intangible assets, goodwill, and R&D all contribute positively to non-commonalities in firm-level earnings. We also find evidence that R&D investment engenders even greater earnings non-commonalities for those industries where patents and other legal mechanisms are most effective in protecting R&D innovations. This finding suggests that appropriability conditions affect the extent to which intangible investments contribute to economic differentiation, as measured by earnings non-commonality. In addition,

[29] Specifically, we again retain the fourth calendar quarter of each firm-year and then form separate non-overlapping subsamples using observations that are five years or 20 calendar quarters apart. This procedure yields five separate non-overlapping subsamples beginning in each year from 1980 to 1984. For example, the subsample beginning in 1980 contains observations for the six calendar years: 1980, 1985, 1990, 1995, 2000, and 2005. The subsample beginning in 1981 follows a similar five-year pattern. Note that the subsamples beginning in 1982, 1983, and 1984 contain observations for only five calendar years since our sample period ends in 2006.

separable recognized intangible assets contribute more to earnings non-commonality than either goodwill or R&D investment. This finding may be attributable to the fact that separable recognized intangible assets are more likely to arise from contractual or legal rights and, therefore, may be less susceptible to expropriation by rival firms, which might lead to commonalities in economic returns.

We document similar associations between intangible intensity and non-commonality in stock returns, with the exception of R&D, which is negatively related to returns non-commonality. This result is consistent with the extensive literature on R&D spillovers and suggests that, even though R&D allows firms to economically differentiate themselves in the short run (as demonstrated by our earnings non-commonality tests), investors anticipate R&D to engender commonalities among firms in the long run. Finally, we document that the intensity and type of intangible assets a firm invests in affects the performance of the market- and industry-based profitability forecast models examined by Fairfield et al. (2009), demonstrating the implications of our findings for the relative importance of market-wide and industry-wide information when forecasting an individual firm's earnings.

In addition to furthering our understanding of the economic determinants of the idiosyncratic component of firms' earnings performance, this study has implications for forecasting the earnings of intangible-intensive firms. Specifically, our finding that intangible investment leads to firm-level earnings that are less dependent on market and industry factors suggests that firm-specific information is likely to be of relatively greater importance in forecasting the earnings of intangible-intensive firms.

Furthermore, our results are relevant to assessing the validity of standard setters' concerns about the lack of controllability of intangible assets. Specifically, our finding that intangible investments contribute positively to earnings non-commonality suggests that intangible assets do not act primarily as pure public goods and thus, may alleviate concerns about controllability issues surrounding intangible assets. However, our differential results for recognized intangibles versus R&D capital suggest that concerns about the controllability of R&D investments may be justified. Finally, our results indicate that the economic impact of intangible assets on earnings non-commonality — in particular R&D capital — depends not only on their fundamental properties, but also on the strength of mechanisms used to protect these assets.

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Appendix
Variable Definitions

UNEXPLAINED = 1 minus the R^2 obtained from estimating the following model over the 20 calendar quarters (requiring a minimum of 10 observations) preceding and including quarter *t* for firm *i*:

$$ROA_{i,t} = \alpha_0 + \alpha_1 MKTROA_{i,t} + \alpha_2 INDROA_{i,t} + \varepsilon_{i,t}$$

where:

$ROA_{i,t}$ = return on assets for firm *i* during calendar quarter *t*, measured as reported income before extraordinary items (data item IBQ) plus quarterly R&D expense (data item XRDQ) less the estimated R&D amortization expense in calendar quarter *t*, scaled by the sum of total recognized assets (*ASSETS*, data item ATQ) and estimated R&D capital (*RDCAPITAL*) as of the beginning of calendar quarter *t*. *RDCAPITAL* is a self-constructed measure of the unamortized cost of R&D investment using current and past R&D expenditures amortized at an annual rate of 20% (i.e., assuming a five-year useful life and straight-line depreciation).

$MKTROA_{i,t}$ = the weighted average ROA (adjusted for R&D capitalization) during calendar quarter *t* for all Compustat firms excluding those in the same two-digit SIC code as firm *i*, measured as the sum of adjusted income before extraordinary items for all Compustat firms excluding firm *i* in calendar quarter *t* scaled by the sum of total recognized assets and estimated R&D capital as of the beginning of calendar quarter *t* for all Compustat firms excluding firm *i*;

$INDROA_{i,t}$ = the weighted average ROA (adjusted for R&D capitalization) during calendar quarter *t* for all Compustat firms excluding firm *i* in the same two-digit SIC code, measured as the sum of adjusted income before extraordinary items for all Compustat firms in the same 2-digit SIC code excluding firm *i* scaled by the sum of total recognized assets and estimated R&D capital as of the beginning of calendar quarter *t* for all Compustat firms in the same 2-digit SIC code excluding firm *i*.

NONCOMMON = $log\left(\frac{UNEXPLAINED_{i,t}}{1-UNEXPLAINED_{i,t}}\right)$

UNEXPLAINED_RET = 1 minus the R^2 obtained from estimating the following model over the 60 calendar months (requiring a minimum of 40 observations) preceding and including month *t* for firm *i*:

$$RET_{i,t} = \alpha_0 + \alpha_1 MKTRET_{i,t} + \alpha_2 INDRET_{i,t} + \varepsilon_{i,t}$$

where:

$RET_{i,t}$ = the market return for firm *i* in month *t*

$MKTRET_{i,t}$ = the value-weighted average *RET* for all CRSP firms during calendar month *t* (excluding the *RET* of those firms in the same two-digit SIC code as firm *i*);

Appendix continued

$INDRET_{i,t}$ = the value-weighted average *RET* for all CRSP firms in the same two-digit SIC code as firm *i* during calendar month *t* (excluding the *RET* of firm *i*).

$$\textbf{\textit{NONCOMMON\_RET}} = log\left(\frac{UNEXPLAINED\_RET_{i,t}}{1-UNEXPLAINED\_RET_{i,t}}\right)$$

INTANGIBLEINTENSITY = the average intangible intensity for firm *i*, where the average is calculated over the number of quarters with non-missing data (*N*) comprising the estimation period used to calculate *UNEXPLAINED* and *NONCOMMON*. The average intangible intensity measure is calculated as:

$$\frac{\sum_{q=-19}^{0}\left(\frac{INTANGIBLES_{i,t+q}}{ASSETS_{i,t+q}+RDCAPITAL_{i,t+q}}\right)}{N}$$

where *INTANGIBLES* = (*SEPARABLE* + *GOODWILL* + *RDCAPITAL*) and *N* = the number of non-missing observations over the 20 quarter period. *SEPARABLE* is the amount of separable recognized intangible assets (excluding goodwill, data item INTANQ); *GOODWILL* is the amount of recognized goodwill (data item GDWLQ); *RDCAPITAL* is the estimated unamortized cost of R&D investment; and *ASSETS* is total recognized assets (data item ATQ).

SEPARABLEINTENSITY = the average asset intensity for separable recognized intangibles for firm *i*, where the average is calculated over the number of quarters with non-missing data (*N*) comprising the estimation period used to calculate *UNEXPLAINED* and *NONCOMMON*:

$$\frac{\sum_{q=-19}^{0}\left(\frac{SEPARABLE_{i,t+q}}{ASSETS_{i,t+q}+RDCAPITAL_{i,t+q}}\right)}{N}$$

GOODWILLINTENSITY = the average goodwill intensity for firm *i*, where the average is calculated over the number of quarters with non-missing data (*N*) comprising the estimation period used to calculate *UNEXPLAINED* and *NONCOMMON*:

$$\frac{\sum_{q=-19}^{0}\left(\frac{GOODWILL_{i,t+q}}{ASSETS_{i,t+q}+RDCAPITAL_{i,t+q}}\right)}{N}$$

RDINTENSITY = the average R&D capital intensity for firm *i*, where the average is calculated over the number of quarters with non-missing data (*N*) comprising the estimation period used to calculate *UNEXPLAINED* and *NONCOMMON*:

$$\frac{\sum_{q=-19}^{0}\left(\frac{RDCAPITAL_{i,t+q}}{ASSETS_{i,t+q}+RDCAPITAL_{i,t+q}}\right)}{N}$$

Appendix continued

MB = the average quarterly market-to-book ratio for firm *i*, where the average is calculated over the number of quarters with non-missing data (*N*) comprising the estimation period used to calculate *UNEXPLAINED* and *NONCOMMON*.

MVE = the average market value of equity of firm *i*, where the average is calculated over the number of quarters with non-missing data (*N*) comprising the estimation period used to calculate *UNEXPLAINED* and *NONCOMMON*.

MKTSHARE = the average market share of firm *i* over the number of quarters with non-missing data (*N*) comprising the estimation period used to calculate *UNEXPLAINED* and *NONCOMMON*, where the market share for each quarter is calculated as firm *i*'s sales (data item SALEQ) divided by the total sales of the two-digit SIC code in which firm *i* operates.

STDROA = the standard deviation of return on assets (*ROA*) for firm *i* measured over the number of quarters with non-missing data (*N*) comprising the estimation period used to calculate *UNEXPLAINED* and *NONCOMMON*.

DIVERS = the average quarterly revenue-based Herfindahl index of firm diversification using the reported business segments of firm *i*, where the average is measured using the number of quarters with non-missing data (*N*) comprising the estimation period used to calculate *UNEXPLAINED* and *NONCOMMON*.

HERF = the average quarterly revenue-based Herfindahl index of industry-level concentration, where the average is calculated over the number of quarters with non-missing data (*N*) comprising the estimation period used to calculate *UNEXPLAINED* and *NONCOMMON*.

LEVERAGE = the average quarterly ratio of long-term debt (data item DLTTQ) to total assets (data item ATQ) for firm *i*, where the average is calculated over the number of quarters with non-missing data (*N*) comprising the estimation period used to calculate *UNEXPLAINED* and *NONCOMMON*.

NIND = the average number of firms used to estimate the quarterly industry ROA index (*INDROA*), where the average is calculated over the number of quarters with non-missing data (*N*) comprising with the estimation period used to calculate *UNEXPLAINED* and *NONCOMMON*.

REG = "1" if firm *i* operates in a regulated industry, defined as the two-digit SIC codes 62 (financial institutions) and 49 (utilities); and "0" otherwise.

NREV = the average annual number of forecast revisions of one-year ahead earnings, where the average is calculated over the number of quarters with non-missing data (*N*) comprising the estimation period used to calculate *UNEXPLAINED* and *NONCOMMON*.

Δ***INST*** = the average of the annual absolute value of the change in the number of shares held by institutional owners scaled by annual trading volume, where the average is calculated over the number of quarters with non-missing data (*N*) comprising the estimation period used to calculate *UNEXPLAINED* and *NONCOMMON*.

TRADES = the average of the annual absolute value of the total shares purchased by insiders less total shares sold by insiders scaled by annual trading volume, where the average is calculated over the number of quarters with non-missing data (N) comprising the estimation period used to calculate *UNEXPLAINED* and *NONCOMMON*.

Table 1

Industry Distribution

2-digit SIC Code	Industry Name	Total Firm-Years	Percent
1	Agricultural Production Crops	295	0.25
2	Agriculture production livestock and animal specialties	51	0.04
7	Agricultural Services	83	0.07
8	Forestry	46	0.04
10	Metal Mining	1314	1.1
12	Coal Mining	151	0.13
13	Oil and Gas Extraction	5425	4.54
14	Mining and quarrying of Nonmetalic Minerals	279	0.23
15	Building Construction	1072	0.9
16	Heavy Construction	358	0.3
17	Construction Special Trade Contractors	397	0.33
20	Food and Kindred Products	2313	1.94
21	Tobacco Products	67	0.06
22	Textile Mill Products	962	0.81
23	Apparel	1229	1.03
24	Lumber and Wood Products, except furniture	763	0.64
25	Furniture and Fixtures	842	0.7
26	Paper and Allied Products	1329	1.11
27	Printing, Publishing, and Allied Industries	1433	1.2
28	Chemicals and Allied Products	7805	6.53
29	Petroleum Refining and Related Industries	866	0.73
30	Rubber and Miscellaneous Plastic Products	1567	1.31
31	Leather and Leather Products	440	0.37
32	Stone, Clay, Glass, and Concrete Products	760	0.64
33	Primary Metal Industries	1933	1.62
34	Fabricated Metal Products, except Machinery and Transportation Equip.	1918	1.61
35	Industrial and Commercial Machinery and Computer Equipment	7937	6.65
36	Electronic and Other Electrical Equipment and Components	9385	7.86
37	Transportation Equipment	2509	2.1
38	Measuring Instruments, Photographic, Medical and Optical Goods	7308	6.12
39	Miscellaneous Manufacturing	1320	1.11
40	Railroad Transportation	393	0.33
41	Local and Suburban Transit	64	0.05
42	Motor Freight Transportation and Warehousing	853	0.71
44	Water Transportation	453	0.38
45	Air Transportation	867	0.73
46	Pipelines, Except Natural Gas	51	0.04

Table 1 continued

2-digit SIC Code	Industry Name	Total Firm-Years	Percent
47	Transportation Services	372	0.31
48	Communications	2939	2.46
49	Electric, Gas, and Sanitary Services	5201	4.35
50	Wholesale Trade - Durable Goods	3202	2.68
51	Wholesale Trade - Non-durable Goods	1619	1.36
52	Building Materials	329	0.28
53	General Merchandise Stores	962	0.81
54	Food Stores	882	0.74
55	Automotive Dealers and Gasoline Service Stations	382	0.32
56	Apparel and Accessory Stores	1058	0.89
57	Home Furniture, Furnishings, and Equipment Stores	670	0.56
58	Eating and Drinking Places	1904	1.59
59	Miscellaneous Retail	1997	1.67
60	Depository Institutions	137	0.11
61	Non-depository Credit Institutions	1363	1.14
62	Security and Commodity Brokers, Dealers	1499	1.26
63	Insurance Carriers	3170	2.65
64	Insurance Agents	530	0.44
65	Real Estate	1610	1.35
67	Holding and Other Investment Offices	5182	4.34
70	Hotels	541	0.45
72	Personal Services	290	0.24
73	Business Services	11606	9.72
75	Automotive Repair	262	0.22
76	Miscellaneous Repair	103	0.09
78	Motion Pictures	1023	0.86
79	Amusement and Recreation Services	1069	0.9
80	Health Services	2095	1.75
81	Legal Ser vices	9	0.01
82	Educational Services	329	0.28
83	Social Services	194	0.16
87	Engineering, Accounting, Research, Management and Related Services	2069	1.73
	Total	119,436	100.00

Table 2

Descriptive Statistics

Variable	**Number of Observations**	**Mean**	**Standard Deviation**	**Lower Quartile**	**Median**	**Upper Quartile**
Earnings Non-commonality Measures:						
UNEXPLAINED	119,436	0.760	0.194	0.642	0.807	0.918
NONCOMMON	119,436	1.586	1.468	0.583	1.432	2.410
Returns Non-commonality Measures:						
UNEXPLAINED_RET	41,312	0.785	0.163	0.693	0.824	0.913
NONCOMMON_RET	41,312	1.662	1.271	0.812	1.544	2.351
Intangible Intensity Measures:						
INTANGIBLEINTENSITY	119,436	0.125	0.160	0.000	0.052	0.210
log(1+*INTANGIBLEINTENSITY*)	119,436	0.111	0.131	0.000	0.057	0.191
SEPARABLEINTENSITY	119,436	0.013	0.051	0.000	0.000	0.002
log(1+*SEPARABLEINTENSITY*)	119,436	0.012	0.043	0.000	0.000	0.002
GOODWILLINTENSITY	119,436	0.041	0.091	0.000	0.000	0.034
log(1+*GOODWILLINTENSITY*)	119,436	0.037	0.077	0.000	0.000	0.034
RDINTENSITY	119,436	0.071	0.126	0.000	0.000	0.095
log(1+*RDINTENSITY*)	119,436	0.063	0.106	0.000	0.000	0.091
MB	119,436	4.383	47.987	1.155	1.880	3.322
log(MB)	119,436	0.717	0.909	0.144	0.631	1.201

Table 2 continued

Variable	Number of Observations	Mean	Standard Deviation	Lower Quartile	Median	Upper Quartile
Control Variables:						
MVE	119,436	1,190.898	7,152.076	21.441	87.366	423.299
log(*MVE*)	119,436	4.616	2.117	3.065	4.470	6.048
MKTSHARE	119,436	0.011	0.043	0.000	0.001	0.004
STDROA	119,436	0.102	2.760	0.009	0.020	0.045
DIVERS	119,436	0.874	0.856	0.756	1.000	1.000
log(1+*DIVERS*)	119,436	0.616	0.130	0.563	0.693	0.693
HERF	119,436	0.094	0.092	0.042	0.063	0.108
log(1+*HERF*)	119,436	0.087	0.076	0.041	0.061	0.102
LEVERAGE	119,436	40.674	360.863	0.265	2.318	16.001
log(1+LEVERAGE)	119,436	1.722	1.696	0.235	1.199	2.833
REG	119,436	0.056	0.230	0.000	0.000	0.000
NIND	119,436	255.914	217.564	80.250	203.000	387.000
log(*NIND*)	119,436	5.113	1.034	4.390	5.310	5.960
NREV	41,312	34.704	46.205	6.000	17.667	44.600
log(1+NREV)	41,312	2.859	1.283	1.946	2.927	3.820
Δ*INST*	41,312	0.137	0.250	0.055	0.093	0.160
log(1+ΔINST)	41,312	0.119	0.118	0.053	0.089	0.148
TRADES	41,312	0.054	1.383	0.002	0.006	0.020
log(1+TRADES)	41,312	0.031	0.117	0.002	0.006	0.020

Notes: See Appendix 1 for variable definitions.

Table 3

Correlation Matrix

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*	*(13)*	*(14)*	*(15)*	*(16)*	*(17)*	*(18)*
(1) NONCOMMON		**0.10**	**0.01**	**-0.10**	**-0.03**	**0.01**	**0.02**	**-0.01**	**-0.07**	**0.02**	**0.02**	**0.03**	**0.02**	0.00	**0.03**	**-0.11**	**-0.03**	**0.02**
(2) NONCOMMON_RET	**0.11**		**-0.09**	**-0.45**	**-0.13**	**0.01**	**0.14**	0.01	**-0.28**	**-0.09**	**0.01**	**0.04**	**0.03**	**0.06**	**-0.01**	**-0.47**	**0.02**	**0.11**
(3) log(*MB*)	0.00	**-0.11**		**0.20**	**-0.04**	**0.02**	**0.12**	**-0.07**	**-0.15**	**-0.09**	**0.22**	**0.32**	**0.08**	**0.04**	**0.34**	**0.14**	**-0.09**	**-0.02**
(4) log(*MVE*)	**-0.11**	**-0.47**	**0.22**		**0.28**	**-0.02**	**-0.27**	**-0.16**	**0.68**	**0.11**	0.00	**0.06**	**0.06**	**0.15**	**-0.05**	**0.73**	**0.12**	**-0.13**
(5) MKTSHARE	**-0.09**	**-0.29**	**-0.21**	**0.60**		**-0.01**	**-0.15**	**0.27**	**0.32**	**-0.02**	**-0.35**	**-0.06**	**0.00**	**0.04**	**-0.11**	**0.22**	**0.05**	**-0.03**
(6) STDROA	**0.08**	**0.17**	**0.27**	**-0.41**	**-0.50**		**0.01**	0.00	**-0.02**	**-0.01**	**0.01**	**0.01**	0.00	0.00	**0.01**	**-0.01**	0.00	0.00
(7) log(1+*DIVERS*)	**0.01**	**0.12**	**0.13**	**-0.26**	**-0.30**	**0.23**		**0.04**	**-0.33**	**-0.04**	**0.07**	**0.04**	**0.00**	**-0.11**	**0.13**	**-0.17**	**-0.10**	**0.05**
(8) log(1+*HERF*)	**-0.02**	0.01	**-0.10**	**-0.21**	**0.23**	**0.03**	**0.06**		**-0.06**	**-0.11**	**-0.45**	**-0.18**	**-0.05**	**-0.02**	**-0.20**	**-0.05**	**0.02**	**0.03**
(9) log(1+*LEVERAGE*)	**-0.07**	**-0.26**	**-0.18**	**0.58**	**0.66**	**-0.46**	**-0.34**	**-0.05**		**0.21**	**-0.20**	**-0.15**	**0.06**	**0.15**	**-0.31**	**0.44**	**0.15**	**-0.06**
(10) REG	**0.02**	**-0.09**	**-0.11**	**0.11**	**0.05**	**-0.17**	**-0.06**	**-0.24**	**0.18**		**0.02**	**-0.15**	**-0.02**	**-0.06**	**-0.13**	**0.02**	**0.03**	**-0.03**
(11) log(*NIND*)	**0.03**	**0.03**	**0.26**	**0.00**	**-0.56**	**0.21**	**0.09**	**-0.51**	**-0.26**	**-0.02**		**0.38**	**0.03**	**0.00**	**0.46**	**-0.05**	**-0.11**	**-0.04**
(12) log(1+*INTANGIBLEINTENSITY*)	**0.03**	**0.05**	**0.35**	**0.08**	**-0.25**	**0.25**	**-0.01**	**-0.21**	**-0.16**	**-0.19**	**0.43**		**0.38**	**0.52**	**0.73**	**0.02**	**-0.11**	**-0.02**
(13) log(1+*SEPARABLEINTENSITY*)	**0.02**	**0.04**	**0.17**	**0.14**	**-0.03**	**0.07**	**-0.09**	**-0.12**	**0.04**	**-0.08**	**0.10**	**0.45**		**0.17**	**-0.01**	**0.03**	**-0.01**	**0.01**
(14) log(1+*GOODWILLINTENSITY*)	0.00	**0.05**	**0.09**	**0.21**	**0.15**	**-0.02**	**-0.19**	**-0.03**	**0.17**	**-0.09**	**0.04**	**0.51**	**0.42**		**-0.10**	**0.09**	**0.01**	**0.03**
(15) log(1+*RDINTENSITY*)	**0.02**	**-0.02**	**0.32**	**-0.01**	**-0.38**	**0.25**	**0.07**	**-0.25**	**-0.31**	**-0.18**	**0.55**	**0.70**	**0.13**	0.00		**-0.05**	**-0.14**	**-0.06**
(16) log(1+NREV)	**-0.11**	**-0.50**	**0.18**	**0.75**	**0.47**	**-0.21**	**-0.16**	**-0.03**	**0.41**	**0.02**	**-0.05**	**0.05**	**0.09**	**0.13**	0.00		**0.04**	**-0.11**
(17) log(1+ΔINST)	**-0.05**	**-0.01**	**-0.15**	**0.28**	**0.35**	**-0.34**	**-0.15**	**0.02**	**0.29**	**0.06**	**-0.19**	**-0.17**	**-0.06**	**0.02**	**-0.21**	**0.07**		**0.14**
(18) log(1+ΔTRADES)	**0.03**	**0.31**	**-0.01**	**-0.37**	**-0.23**	**0.17**	**0.16**	**0.11**	**-0.24**	**-0.12**	**-0.04**	**-0.02**	**-0.01**	**0.01**	**-0.06**	**-0.32**	**0.09**	

Notes:
See Appendix 1 for variable definitions. Pearson (Spearman) correlation coefficients are presented above (below) the diagonal. The coefficients in bold are all statistically significant at the 10% level or lower.

Table 4

Tests of the Association between Intangible Intensity and Earnings Non-commonality

DEPENDENT VARIABLE: *NONCOMMON*

Variable	(1)	(2)	(3)		(4)	(5)	(6)
	Coefficient Estimate	*t*-statistic	*p*-value		Coefficient Estimate	*t*-statistic	*p*-value
Intercept	2.000	17.91	<0.001		1.988	16.73	<0.001
log(1+*INTANGIBLEINTENSITY*)	0.402	4.18	<0.001		—	—	—
log(1+*SEPARABLEINTENSITY*)	—	—	—		0.803	3.87	0.001
log(1+*GOODWILLINTENSITY*)	—	—	—		0.325	2.17	0.040
log(1+*RDINTENSITY*)	—	—	—		0.309	2.82	0.009
log(*MB*)	0.052	4.82	<0.001		0.053	4.93	<0.001
log(*MVE*)	-0.092	-12.77	<0.001		-0.092	-12.73	<0.001
MKTSHARE	0.266	1.17	0.250		0.295	1.292	0.208
STDROA	0.006	1.94	0.064		0.006	1.924	0.066
log(1+*DIVERS*)	-0.161	-1.89	0.071		-0.163	-1.844	0.077
log(1+*HERF*)	-0.270	-1.45	0.159		-0.266	-1.433	0.164
log(1+LEVERAGE)	0.013	1.48	0.150		0.010	1.148	0.262
REG	0.263	4.11	<0.001		0.262	4.091	<0.001
log(*NIND*)	0.003	0.16	0.872		0.006	0.343	0.735
Adjusted R^2	1.46%				1.48%		
Number of Observations	119,436				119,436		

Notes:
See Appendix 1 for variable definitions. The reported *p*-values are two-tailed and are based on robust standard errors adjusted for two-way clustering by firm and calendar year.

Table 5

Impact of Appropriability Conditions on the Association between R&D Intensity and Earnings Non-commonality

DEPENDENT VARIABLE: *NONCOMMON*

Variable	Coefficient Estimate	*t*-statistic	*p*-value
Intercept	2.031	10.433	<0.001
log(1+*SEPARABLEINTENSITY*)	0.840	2.523	0.018
log(1+*GOODWILLINTENSITY*)	0.546	2.170	0.040
log(1+*RDINTENSITY*)	0.284	1.641	0.113
log(1+*RDINTENSITY*)×*LEGALRIGHTS*	0.493	2.317	0.029
LEGALRIGHTS	-0.137	-3.823	0.001
log(*MB*)	0.038	2.676	0.013
log(*MVE*)	-0.093	-9.400	<0.001
MKTSHARE	0.306	0.339	0.737
STDROA	0.010	2.116	0.045
log(1+*DIVERS*)	-0.167	-1.390	0.177
log(1+*HERF*)	-0.687	-1.066	0.296
log(1+LEVERAGE)	-0.010	-0.770	0.449
log(*NIND*)	0.016	0.557	0.583
Adjusted R^2	2.20%		
Number of Observations	51,401		

Notes:

LEGALRIGHTS is a binary variable that equals "1" if the firm operates in an industry with an aggregate effectiveness score that is above the sample median with respect to the effectiveness of patents and other legal protections in protecting R&D innovations; and "0" otherwise. The aggregate effectiveness score for each industry is computed using data based on the 1994 Carnegie Mellon Survey on Industrial R&D as reported in Cohen et al. (2000).

See Appendix 1 for all other variable definitions. The reported *p*-values are two-tailed and are based on robust standard errors adjusted for two-way clustering by firm and calendar year.

Table 6

Tests of the Association between Intangible Intensity and Returns Non-commonality

DEPENDENT VARIABLE: *NONCOMMON_RET*

	(1)	(2)	(3)		(4)	(5)	(6)
Variable	Coefficient Estimate	*t*-statistic	*p*-value		Coefficient Estimate	*t*-statistic	*p*-value
Intercept	3.475	12.897	<0.001		3.186	12.516	<0.001
log(1+*INTANGIBLEINTENSITY*)	0.522	2.273	0.034		—	—	—
log(1+*SEPARABLEINTENSITY*)	—	—	—		0.880	2.979	0.007
log(1+*GOODWILLINTENSITY*)	—	—	—		1.530	5.202	<0.001
log(1+*RDINTENSITY*)	—	—	—		-0.853	-2.884	0.009
log(*MB*)	0.026	1.032	0.314		0.055	2.248	0.036
log(*MVE*)	-0.167	-5.626	<0.001		-0.171	-5.928	<0.001
MKTSHARE	0.109	0.314	0.757		0.584	1.803	0.087
STDROA	0.007	4.323	<0.001		0.007	4.853	<0.001
log(1+*DIVERS*)	0.312	1.601	0.125		0.437	2.418	0.025
log(1+*HERF*)	-0.968	-4.230	<0.001		-1.060	-4.517	<0.001
log(1+LEVERAGE)	0.024	2.184	0.041		-0.006	-0.563	0.580
REG	-0.380	-5.704	<0.001		-0.387	-5.843	<0.001
log(*NIND*)	-0.072	-3.521	0.002		-0.012	-0.761	0.455
NONCOMMON	0.046	6.958	<0.000		0.047	7.277	<0.001
log(1+NREV)	-0.294	-10.102	<0.000		-0.287	-10.492	<0.001
log(1+ΔINST)	0.231	1.356	0.190		0.126	0.756	0.459
log(1+TRADES)	0.482	3.550	0.002		0.414	3.084	0.006
Adjusted R^2	25.62%				27.03%		
Number of Observations	41,312				41,312		

Notes:

See Appendix 1 for variable definitions. The reported *p*-values are two-tailed and are based on robust standard errors adjusted for two-way clustering by firm and calendar year.

Table 7

Impact of Appropriability Conditions on the Association between R&D Intensity and Returns Non-commonality

DEPENDENT VARIABLE: *NONCOMMON_RET*

Variable	Coefficient Estimate	*t*-statistic	*p*-value
Intercept	2.523	7.865	<0.001
log(1+*SEPARABLEINTENSITY*)	0.902	1.892	0.073
log(1+*GOODWILLINTENSITY*)	1.103	2.624	0.016
log(1+*RDINTENSITY*)	-1.683	-3.483	0.002
log(1+*RDINTENSITY*)×*LEGALRIGHTS*	0.868	2.746	0.013
LEGALRIGHTS	0.075	1.456	0.161
log(*MB*)	0.065	1.910	0.071
log(*MVE*)	-0.134	-3.991	0.001
MKTSHARE	-1.175	-1.754	0.095
STDROA	0.001	0.290	0.775
log(1+*DIVERS*)	0.643	3.196	0.005
log(1+*HERF*)	-0.716	-0.947	0.355
*log(*1+*LEVERAGE)*	0.047	2.829	0.010
log(*NIND*)	0.062	2.276	0.034
NONCOMMON	0.035	4.289	<0.001
*log(*1+*NREV)*	-0.338	-9.470	<0.001
*log(*1+Δ*INST)*	0.018	0.065	0.949
*log(*1+*TRADES)*	0.750	3.210	0.004
Adjusted R^2	26.51%		
Number of Observations	19,343		

Notes:

LEGALRIGHTS is a binary variable that equals “1” if the firm operates in an industry with an aggregate effectiveness score that is above the sample median with respect to the effectiveness of patents and other legal protections in protecting R&D innovations; and “0” otherwise. The aggregate effectiveness score for each industry is computed using data based on the 1994 Carnegie Mellon Survey on Industrial R&D as reported in Cohen, Nelson, and Walsh [2000].

See Appendix 1 for all other variable definitions. The reported *p*-values are two-tailed and are based on robust standard errors adjusted for two-way clustering by firm and calendar year.

Table 8

Tests of the Associations between Intangibles and Profitability Forecast Improvements from Market-Wide and Industry-Specific Models

Panel A: Summary of Profitability Forecast Improvements

	Market-wide vs. Random-Walk			Industry-specific vs. Market-wide	
	Value	p-value		Value	p-value
Mean Improvement	0.003	<0.001		0.000	0.727
Median Improvement	0.001	<0.001		0.000	0.273
N	87,865			87,865	

Panel B: DEPENDENT VARIABLE: *IMPROVE_MKT*

Variable	Coefficient Estimate	*t*-statistic	*p*-value		Coefficient Estimate	*t*-statistic	*p*-value
Intercept	0.003	14.32	<0.001		0.003	14.09	<0.001
log(1+*INTANGIBLEINTENSITY*)	-0.002	-1.59	0.111		—	—	—
log(1+*SEPARABLEINTENSITY*)	—	—	—		-0.005	-1.87	0.061
log(1+*GOODWILLINTENSITY*)	—	—	—		-0.006	-3.05	0.002
log(1+*RDINTENSITY*)	—	—	—		0.004	2.05	0.040
Adjusted R^2	0.00%				0.02%		
Number of Observations	87,865				87,865		

Table 8 continued

Panel C: DEPENDENT VARIABLE: *IMPROVE_IND*

Variable	Coefficient Estimate	*t*-statistic	*p*-value		Coefficient Estimate	*t*-statistic	*p*-value
Intercept	-0.000	-1.46	0.144		-0.000	-1.78	0.074
log(1+*INTANGIBLEINTENSITY*)	0.001	1.85	0.065		—	—	—
log(1+*SEPARABLEINTENSITY*)	—	—	—		0.001	1.49	0.135
log(1+*GOODWILLINTENSITY*)	—	—	—		-0.004	-5.18	<0.001
log(1+*RDINTENSITY*)	—	—	—		0.005	6.79	<0.001
Adjusted R^2	0.00%				0.08%		
Number of Observations	87,865				87,865		

Notes:

IMPROVE_MKT is the forecast accuracy improvement from a market-wide prediction model of return on net operating assets relative to a naive random-walk expectation model.

IMPROVE_IND is the forecast accuracy improvement from an industry-specific prediction model of return on net operating assets relative to a market-wide prediction model.

See Appendix 1 for all other variable definitions. The reported *p*-values are two-tailed and are clustered by firm.