Rev Account Stud (2011) 16:539–573
DOI 10.1007/s11142-011-9151-x

Intangible investment and the importance of firm-specific factors in the determination of earnings

Nerissa C. Brown · Michael D. Kimbrough

Published online: 19 May 2011

Abstract We examine the effect of intangible investment on earnings noncommonality, defined as the extent to which a firm's earnings performance is determined by firm-specific factors versus market and industry factors. Such insight is important in determining the appropriate weighting of these factors when forecasting a firm's earnings. For a sample of US firms over the 1980–2006 period, we find that earnings noncommonality is positively associated with intangible asset intensity. This finding is consistent with the resource-based view of the firm, which posits that intangible investments allow firms to differentiate themselves economically from their rivals. We also find that separable recognized intangibles contribute more to earnings noncommonality than do either goodwill or R&D, perhaps because separable recognized intangibles are more likely to arise from contractual or legal rights and thus are less susceptible to expropriation by rival firms. Finally, we find that the positive impact of R&D on earnings noncommonality 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 a differentiation strategy depends largely on the effectiveness of mechanisms used to protect intangible investments from expropriation.

Keywords Earnings noncommonality · Intangible assets · Appropriability

JEL Classification L25 · M41 · O3

N. C. Brown
J. Mack Robinson College of Business, Georgia State University, Atlanta, GA 30303, USA
e-mail: nbrown@gsu.edu

M. D. Kimbrough (✉)
Robert H. Smith School of Business, University of Maryland, College Park, MD 20742-1871, USA
e-mail: mkimbrough@rhsmith.umd.edu

1 Introduction

We examine the effect of intangible investment on earnings noncommonality, defined as the extent to which a firm's earnings performance is determined by firm-specific factors rather than market- and industry-level factors (Ball and Brown 1967; Gonedes 1973; Magee 1974). Following prior research (Morck et al. 2000; Elgers et al. 2004; Piotroski and Roulstone 2004), we measure earnings noncommonality as the log 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 noncommonality measure are consistent with firm-level earnings that are more (less) dependent on firm-specific factors. Evidence on the determinants of earnings noncommonality is important to understanding the appropriate weighting of market-level, industry-level, and firm-specific factors when forecasting a firm's earnings (Gonedes 1973; Fairfield et al. 2009).

We focus on intangible investment because it likely affects the degree of noncommonality in firm-level earnings, although the direction of the effect is unclear. In particular, the resource-based view of the firm articulated in the strategy literature posits that intangible investments are critical drivers of a differentiation strategy that creates sustainable advantages over rival industry firms (for example, Lippman and Rumelt 1982; Rumelt 1984; Itami 1987; Dierickx and Cool 1989; Barney 1991). On the other hand, the industrial organization literature emphasizes that intangible resources are susceptible to expropriation or imitation by rivals because these resources are nonrival and nonexcludable. In this regard, they are like public goods from which multiple firms can benefit.[2] Hence, intangible investments could lead to either lesser or greater commonality or comovement in firm profitability.

For a sample of US firms over the 1980–2006 period, we find a positive relation between a firm's intangible asset intensity and earnings noncommonality, consistent with the dominance of the resource-based view. We also examine the individual contribution of various classes of intangible investments—goodwill, separable recognized intangible assets (other than goodwill), and the estimated unamortized cost of R&D investment. We find that all three forms of intangibles contribute positively to earnings noncommonality, with separable recognized intangibles contributing more than either goodwill or R&D investment. This result may be attributable to separable recognized intangibles being more likely to arise from contractual or legal rights and thus less susceptible to expropriation by rivals.

Prior research on R&D spillovers (e.g., Arrow 1962; Jaffe 1986; Levin et al. 1987; Cockburn and Griliches 1988; Davis 2001) suggests that the lower association between R&D investment and earnings noncommonality (that is, relative to separable recognized intangibles) reflects the greater susceptibility of R&D to

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

[2] The nonrival attribute of intangibles refers to the originating firm's ability to use such resources without impairing the potential usefulness (or scarcity) of the same resource to external firms (Romer 1990). Intangibles are non-excludable in that external firms can rarely be precluded from enjoying some of the benefits of these resources.

expropriation by rival firms. Consistent with this interpretation, we find that the positive relation between R&D investment and earnings noncommonality is significantly greater in those industries where patents and other legal mechanisms protect R&D innovations from expropriation.

Highlighting the economic significance of our primary results, we find in supplemental analysis that total intangible asset intensity as well as goodwill and separable recognized asset intensity are positively related to noncommonality in stock returns—similar to their associations with earnings noncommonality. In contrast to our earnings-based tests, however, we find that R&D intensity is negatively related to returns noncommonality. 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 noncommonality tests), investors anticipate R&D to engender commonalities among firms in the long run. Finally, we document that the intensity and type of a firm's intangible investment 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 results for the relative importance of market and industry information in forecasting a firm's earnings.

Our study makes several contributions to the accounting literature. First, we extend the limited evidence on the determinants of earnings noncommonality. 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 evidence implies that firm-specific information is more important in forecasting the earnings of intangible-intensive firms.

Second, our study complements prior research on the relation between intangible investment and various statistical properties of accounting earnings such as earnings persistence (Villalonga 2004) and earnings volatility (Kothari et al. 2002). Our results indicate that intangible investment also has a significant impact on earnings noncommonality.[3] Third, we provide empirical evidence on the relative descriptiveness of the resource-based view versus the public-goods view of intangibles.

Fourth, our evidence on the economic properties of intangibles is relevant in 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 (Lev 2001).[4] With few exceptions, 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; Skinner 2008 for

[3] Prior studies document that earnings commonality 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 2010), the structure of analyst research portfolios and analyst forecast accuracy (De Franco et al. 2011; Kini et al. 2009), and the structure of institutional investors' stock portfolios (Engelberg et al. 2009).

[4] See FASB (1985, para. 26) for a discussion of controllability as related to asset recognition.

further discussion). Our evidence alleviates concerns about the extent to which intangible assets suffer from a lack of controllability. Nonetheless, the differential results for recognized intangibles versus R&D capital suggest that standard setters have identified for recognition those intangibles that are most controllable and that concern about the controllability of R&D capital may be justified. Finally, managers should be interested in our evidence that intangible investments can be a successful element of a firm's differentiation strategy, depending 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 our research questions. Section 3 discusses our variable measurement. 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 and industry 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 accurate forecasting of earnings and other economic outcomes for the firms they follow—incorporate the degree of commonality in firm fundamentals when forecasting firm performance, presumably to exploit scale economies in information acquisition for firms facing similar economic forces. For example, among US institutions, Kini et al. (2009) find that analysts are more likely to specialize within an industry (country) as the commonality 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, Litov et al. (2010) find that firms with unique (common) investment strategies receive less (more) analyst coverage, which in turn leads to a discount (premium) in market value. De Franco et al. (2011) 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. Lastly, Engelberg et al. (2009) find that institutional investors are more likely to hold portfolios of stocks that exhibit greater earnings commonality. Taken together, this body of evidence indicates that greater commonality in firm fundamentals increases the value of market and industry analysis to information intermediaries.[5]

In addition to its importance in forecasting firm performance, earnings noncommonality is linked to several other accounting phenomena. First, prior research documents that earnings noncommonality is positively associated with stock return noncommonality, suggesting that the idiosyncratic component of firm-level earnings (which likely results from firms' unique capabilities and intangible resources) 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. Gong et al. (2009) find that earnings noncommonality across related firms positively impacts the disclosure (and precision) of management earnings forecasts. They also find that investors react more strongly to management forecast news as earnings noncommonality increases. Kimbrough and Wang (2010) find that investors' assessment of a manager's self-serving attributions in quarterly earnings press releases depends on the extent to which the firm's earnings are linked to common market and industry factors.

The preceding discussion highlights that earnings noncommonality is important for forecasting and in a number of other accounting and economic contexts. However, despite this importance, there is surprisingly little evidence on the factors that drive the strength of these (non)commonalities. That is, what drives firm-level earnings to *move together*? We argue that such insight is important because, although prior evidence documents the influence of industry and market factors on firm profitability, there is substantial variation in the documented strength of these influences. For instance, despite evidence of the important influence of industry factors on firm profitability (Schmalensee 1985; McGahan and Porter 1997, 2002), several studies document economically small associations between industry factors and firm profitability (for example, 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 (Rumelt 1991; Mauri and Michaels 1998).

2.2 Theoretical development and research questions

2.2.1 The impact of intangible investments on earnings noncommonality

While there is scant empirical evidence on the factors that influence the noncommonality of earnings across industry firms, the accounting literature (for example, 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

[5] 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.

intangible investments such as those related to superior customer service, brand image, R&D, and control systems focused on creativity and innovation are key to 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).[6]

The focus on intangible investments as a source of economic differentiation is consistent with the resource-based view, which posits that a firm's endowment of resources is a significant determinant of its ability to achieve and sustain competitive advantages. More specifically, under the resource-based view intangible resources are a key source of competitive advantage (Lippman and Rumelt 1982; Hall 1993) because they are hard to acquire or develop internally (Itami 1987) and are more difficult for rival firms to replicate as a result (Rumelt 1984; Nelson 1991). Under this perspective, intangible resources drive heterogeneity or noncommonality in economic performance among firms (Mauri and Michaels 1998). Consistent with the resource-based view, Villalonga (2004) finds that firms with high intangible resource intensity, as proxied by Tobin's Q, have more persistent earnings streams.

An alternative view 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 Teece 1986; Dosi 1988; Lev 2001). Under this 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), a share of the profits from innovative investments often spills 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).[7]

Intangible assets differ from tangible assets in two important respects that have considerable implications for the susceptibility of intangibles to expropriation. First, intangibles are nonrival in nature—that is, an originating firm's use of an intangible resource does not impair the potential usefulness (or scarcity) of the same resource to external firms (Romer 1990). A major contributing factor to this nonrivalry attribute is that intangibles are not limited by the diminishing returns to scale typical of tangible assets. In fact, intangible assets often experience increasing returns to scale and can be leveraged to create value to a greater degree than tangible assets (Lev 2001). Second, intangible assets are only partially excludable. That is, non-owners can rarely be prevented from enjoying some of the benefits of intangible investments (Lev 2001). This attribute is in contrast to tangible resources where well-defined property rights enable owners to effectively exclude others from enjoying the benefits of these resources. This partial excludability characteristic, 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

[6] See Chap. 2, p. 9.

[7] 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.

assets.[8] These diffusion forces include employee mobility and the competitive intelligence activities of rivals.[9,10]

In summary, the resource-based view literature argues that intangible investments are hard to replicate and thus result in heterogeneity or noncommonality in firms' earnings performance. Alternatively, the industrial organization literature posits that, because intangible assets are susceptible to expropriation, they can 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 earnings noncommonality?

2.2.2 *The differential impact of various classes of intangibles on earnings noncommonality*

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 benefit (Arrow 1962; Jaffe 1986; Levin et al. 1987; Cockburn and Griliches 1988; Davis 2001). Prior research suggests that rivals can benefit from a firm's R&D by engaging in 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

[8] 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).

[9] 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. Prior evidence also suggests that intangible-intensive firms view employee mobility as a competitive threat. For instance, Moen (2005) finds that high technology firms pay lower wages to knowledge workers in anticipation that such workers will expose the firm's innovative activities once they leave. Erkens (2010) finds that the use of stock options as a retention tool is greater for R&D-intensive firms, consistent with such firms being concerned about the threat of spillover due to employee turnover. Lastly, prior studies document innovative firms' use of non-competition agreements to prevent spillovers due to employee mobility (Gilson 1999; Marx et al. 2009).

[10] Competitive intelligence is the "methodical acquisition, analysis, and evaluation of information about competitors, both known and potential" (Von Hoffman 1999, p. 3), which is predicated on the notion that firms can successfully profit from knowledge of other firms' resources and that these resources are exploitable. 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, 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 (e.g., Levin et al. 1987; Mansfield 1985; Cockburn and Griliches 1988; Cohen et al. 2002) corroborate that managers seek out information about their rivals' R&D efforts. Mansfield (1985) finds that development decisions are in the hands of rivals within 12–18 months and that information about new products or processes leaks out within a year. Cohen et al. (2002) report that 16% (44%) of surveyed firms in the US (Japan) are aware of their rivals' R&D projects before the development stage.

generating their own innovations but also to develop absorptive capacity that allows them to identify, assimilate, and exploit knowledge from rival firms as well as the ability to imitate new 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). Therefore, R&D investment may engender relatively less earnings noncommonality.

In contrast to R&D investments, recognized intangible assets (with the exception of goodwill) must arise from contractual rights or be separable 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* noncommonality 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 firms' 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* earnings noncommonality (relative to R&D).[11]

Based on the foregoing discussion, we examine the differential impact of various classes of intangible investment on the degree of earnings noncommonality as stated below:

RQ2: Do the various classes of recognized and unrecognized intangible investments differentially affect the degree of earnings noncommonality?

2.2.3 Property rights and the impact of intangibles on earnings noncommonality

The extent to which intangible resources are vulnerable to expropriation is a function of not only their previously discussed fundamental economic properties but also the strength of the surrounding property rights enforcement regime (Teece 1986). Intangible investments are more likely to increase the extent of earnings noncommonality if innovative firms can effectively enforce property rights such that rival firms cannot readily benefit from the investments.[12] While patents and copyrights provide property rights protection over original ideas, the effectiveness of these mechanisms is unclear given the abundance of patent lawsuits (Lev 2001), the possibility that imitators can circumvent patents by legally inventing around

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

[12] This argument is also consistent with Matolcsy and Wyatt (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.

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 investment contributes to earnings noncommonality. Therefore we examine the following research question:

RQ3: Does the strength of legal property rights affect the relation between intangible investment and the degree of earnings noncommonality?

3 Variable measurement

3.1 Measurement of earnings noncommonality

We estimate the idiosyncratic component of a firm's earnings performance (earnings noncommonality) based on the methodology outlined in prior studies (Morck et al. 2000; Durnev et al. 2004; Piotroski and Roulstone 2004; Elgers et al. 2004). This approach estimates the portion of a firm's earnings that cannot be explained by market or industry earnings.[13] 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):

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

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 (*RDCAP*) 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

[13] This methodology is similar to that used in prior studies to estimate comovement or noncommonalities in stock returns (see Morck et al. 2000; Durnev et al. 2004; Piotroski and Roulstone 2004). We also use this methodology to construct our measure of stock return noncommonality as outlined in Sect. 5.2.1.

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 estimate R&D capital (*RDCAP*) each year as the unamortized cost of R&D investment using current and past R&D expenditures amortized at an annual rate of 20% (assuming a 5-year useful life and straight-line depreciation).[14] 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[15] and quarterly R&D amortization.[16]

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.[17] We then define earnings noncommonality as the unexplained portion of the firm's *ROA* (*UNEXPLAINED*), which is 1 minus the R^2 from each firm-specific regression of Eq. 1. Lastly, following prior research (Piotroski and Roulstone 2004), we create an unbounded continuous variable for each firm-quarter using the log transformation of *UNEXPLAINED* as defined below:

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

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

14 This treatment is also consistent with Lev and Sougiannis (1996), who report that the useful life of R&D capital is, on average, 5–7 years for most industries.

15 We obtain quarterly R&D expenditures from Compustat, 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 occur 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.

16 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.

17 Our results and inferences are unchanged when we use four-digit SIC codes as well as the Fama–French industry categories to classify industries.

industry-level factors. The appendix summarizes the earnings noncommonality measure and each of the variables discussed below.[18]

3.2 Measurement of firm-level intangible resources

To capture the firm's total investment in intangible resources (*INTANG*), we aggregate for each quarter the firm's investments in separable recognized intangible assets (except goodwill, *SEPRBL*), goodwill (*GDWL*), and R&D capital (*RDCAP*). *SEPRBL* and *GDWL* 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 that has been examined by several accounting studies (for example, Barth and Kasznik 1999; Barth et al. 2001; Lev and Sougiannis 1996; Kothari et al. 2002).[19]

For each quarter t, we compute the firm's average intangible asset intensity (*INTANGINT*) as *INTANG* scaled by the sum of *ASSETS* and *RDCAP* and then take the average over the 20-quarter period used to estimate *NONCOMMON*. That is:

$$INTANGINT_{i,t} = \frac{\sum_{q=-19}^{0}\left(\frac{INTANG_{i,t+q}}{ASSETS_{i,t+q}+RDCAP_{i,t+q}}\right)}{N} \tag{3}$$

where *INTANG* equals ($SEPRBL + GDWL + RDCAP$), and N is the number of nonmissing observations over the 20-quarter period. We calculate an average intensity measure over the same 20-quarter period used to estimate Eq. 1 to ensure consistency in the measurement period of all of our regression variables.

We use analogous procedures (see "Appendix") to calculate the average quarterly intensity for the separate components of recognized and unrecognized intangibles (*SEPRBLINT*, *GDWLINT*, and *RDINT*). 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 *INTANGINT* measure. The market-to-book ratio uses the firm's market value as a basis for inferring the value of intangible resources not accorded accounting recognition as well as the value of R&D investments omitted from our *RDCAP* estimate (for

[18] Our earnings noncommonality measure is qualitatively similar to that used in De Franco et al. (2011) and Gong et al. (2009). De Franco et al. (2011) 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 (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).

[19] We do not examine advertising as a separate class of intangibles for the following reasons: First, the data for quarterly advertising expenditures are even sparser in Compustat. Second, prior studies report that the benefits of advertising are short-lived, lasting for only a few months or 1 year (Peles 1970; Lev and Sougiannis 1996).

example, write-offs of purchased R&D).[20] We acknowledge that our intangible intensity measures as well as the market-to-book ratio do not capture the full complement of firms' intangible resources. Given this limitation, we are cautious in making inferences about the economic significance of the association between intangible investments and earnings noncommonality.

3.3 Control variables

We address each of our research questions by regressing *NONCOMMON* (described in Sect. 3.1) on the intangible intensity measures defined in Sect. 3.2 as well as various control variables suggested by prior research. We describe the measurement of each control variable in the appendix. With the exception of *REG*, all of our regression variables are averaged over the estimation period used to calculate *NONCOMMON*. In addition, we log transform the values of *INTANGINT* and several of our control variables to mitigate the effect of skewness in the distributions of the respective variables.

Consistent with prior research (Morck et al. 2000; Durnev et al. 2003, 2004; Piotroski 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 such firms might move independently of industry and market 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 less earnings noncommonality. 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 noncommonality, 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 are 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 offsetting idiosyncratic results, which in turn could increase the comovement of firm-level earnings. 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

[20] 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.

(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).[21] Prior research also indicates that higher leverage is associated with greater earnings volatility (Beaver et al. 1970; Kothari et al. 2002), thereby resulting in greater earnings noncommonality (Piotroski and Roulstone 2004). We therefore control for firm leverage (*LEVERAGE*) as a possible correlated factor of intangible intensity and earnings noncommonality.

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 (Piotroski 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 noncommonality measure and the size of the industry.[22] Moreover, larger industries may be more mature, contain more homogenous firms and, as such, may exhibit less earnings noncommonality (Durnev et al. 2004).

For our third research question (RQ3), we measure the strength and effectiveness of property rights mechanisms within each industry using the industry-level survey results of Cohen et al. (2000). The survey results reported in Cohen et al. (2000) are based on the 1994 Carnegie Mellon Survey on Industrial R&D in the US 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 1991–1993 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.[23]

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

[21] 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 nondebt tax shield, thereby decreasing the tax advantage of debt financing.

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

[23] 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 structure 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 slightly for large firms, while the effectiveness of patents for process innovations remains stable across all firms.

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 create a comprehensive measure of the effectiveness of property rights protection at the industry level.[24] 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.

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 1980–2006 period. We first eliminate all firm-quarters with missing information for calculating our regression variables. Further, we eliminate firms with a nonclassifiable industry code (SIC 99). We require each firm-quarter to have nonmissing data for at least 10 calendar quarters preceding quarter *t*. To mitigate the potential effect of serial correlation arising from the use of overlapping rolling windows to estimate earnings noncommonality, we conduct our empirical analyses using data only for the fourth calendar quarter of each firm-year.[25] These data restrictions result in a final full sample of 119,436 firm-years for 13,685 unique firms.[26] We use the full sample to assess RQ1 and RQ2. For RQ3, we use a reduced sample of 51,401 firm-years because data for the industry-level *LEGALRIGHTS* measure are available only for the manufacturing industry (SIC 20–39).

4.2 Descriptive evidence

Table 1 summarizes 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)

[24] 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.

[25] As discussed in Sect. 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). In robustness tests (see Sect. 5.2.4), our inferences are unchanged when we conduct our empirical tests using non-overlapping subsamples where each firm-year observation is 20 calendar quarters apart.

[26] 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 the book value of equity. These additional data restrictions attempt to control for firms with possible asset impairments.

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	1,314	1.1
12	Coal mining	151	0.13
13	Oil and gas extraction	5,425	4.54
14	Mining and quarrying of nonmetallic minerals	279	0.23
15	Building construction	1,072	0.9
16	Heavy construction	358	0.3
17	Construction special trade contractors	397	0.33
20	Food and kindred products	2,313	1.94
21	Tobacco products	67	0.06
22	Textile mill products	962	0.81
23	Apparel	1,229	1.03
24	Lumber and wood products, except furniture	763	0.64
25	Furniture and fixtures	842	0.7
26	Paper and allied products	1,329	1.11
27	Printing, publishing, and allied industries	1,433	1.2
28	Chemicals and allied products	7,805	6.53
29	Petroleum refining and related industries	866	0.73
30	Rubber and miscellaneous plastic products	1,567	1.31
31	Leather and leather products	440	0.37
32	Stone, clay, glass, and concrete products	760	0.64
33	Primary metal industries	1,933	1.62
34	Fabricated metal products, except machinery and transportation equipment	1,918	1.61
35	Industrial and commercial machinery and computer equipment	7,937	6.65
36	Electronic and other electrical equipment and components	9,385	7.86
37	Transportation equipment	2,509	2.1
38	Measuring instruments, photographic, medical and optical goods	7,308	6.12
39	Miscellaneous manufacturing	1,320	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
47	Transportation services	372	0.31
48	Communications	2,939	2.46
49	Electric, gas, and sanitary services	5,201	4.35

Table 1 continued

2-digit SIC code	Industry name	Total firm-years	Percent
50	Wholesale trade—durable goods	3,202	2.68
51	Wholesale trade—nondurable goods	1,619	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	1,058	0.89
57	Home furniture, furnishings, and equipment stores	670	0.56
58	Eating and drinking places	1,904	1.59
59	Miscellaneous retail	1,997	1.67
60	Depository institutions	137	0.11
61	Nondepository credit institutions	1,363	1.14
62	Security and commodity brokers, dealers	1,499	1.26
63	Insurance carriers	3,170	2.65
64	Insurance agents	530	0.44
65	Real estate	1,610	1.35
67	Holding and other investment offices	5,182	4.34
70	Hotels	541	0.45
72	Personal services	290	0.24
73	Business services	11,606	9.72
75	Automotive repair	262	0.22
76	Miscellaneous repair	103	0.09
78	Motion pictures	1,023	0.86
79	Amusement and recreation services	1,069	0.9
80	Health services	2,095	1.75
81	Legal services	9	0.01
82	Educational services	329	0.28
83	Social services	194	0.16
87	Engineering, accounting, research, management and related services	2,069	1.73
	Total	119,436	100.00

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.

Table 2 provides descriptive statistics for our regression variables. We winsorize all continuous variables at the 1st and 99th percentiles of the sample distribution to reduce the effect of extreme outliers.[27] The mean (median) of *UNEXPLAINED* from

[27] Our results are robust to the exclusion of observations with absolute value of studentized residuals greater than 3.

Table 2 Descriptive statistics

Variable	Number of observations	Mean	Standard deviation	Lower quartile	Median	Upper quartile
Earnings noncommonality measures						
UNEXPLAINED	119,436	0.760	0.192	0.642	0.807	0.918
NONCOMMON	119,436	1.580	1.423	0.583	1.432	2.410
Returns noncommonality measures						
UNEXPLAINED_RET	41,312	0.786	0.161	0.693	0.824	0.913
NONCOMMON_RET	41,312	1.654	1.227	0.812	1.544	2.351
Intangible intensity measures						
INTANGINT	119,436	0.121	0.151	0.000	0.052	0.205
log(1 + *INTANGINT*)	119,436	0.106	0.126	0.000	0.051	0.186
SEPRBLINT	119,436	0.011	0.036	0.000	0.000	0.002
log(1 + *SEPRBLINT*)	119,436	0.011	0.033	0.000	0.000	0.002
GDWLINT	119,436	0.040	0.085	0.000	0.000	0.034
log(1 + *GDWLINT*)	119,436	0.036	0.074	0.000	0.000	0.034
RDINT	119,436	0.070	0.123	0.000	0.000	0.095
log(1 + *RDINT*)	119,436	0.062	0.104	0.000	0.000	0.091
MB	119,436	3.162	4.294	1.155	1.880	3.322
log(*MB*)	119,436	0.716	0.855	0.144	0.631	1.201
Control variables						
MVE	119,436	855.303	2,667.940	21.441	87.366	423.299
log(*MVE*)	119,436	4.614	2.083	3.065	4.470	6.048
MKTSHARE	119,436	0.009	0.027	0.000	0.001	0.005
STDROA	119,436	0.041	0.063	0.009	0.020	0.045
DIVERS	119,436	0.864	0.207	0.757	1.000	1.000
log(1 + *DIVERS*)	119,436	0.616	0.131	0.563	0.693	0.693
HERF	119,436	0.093	0.088	0.042	0.063	0.108
log(1 + *HERF*)	119,436	0.086	0.074	0.041	0.061	0.102
LEVERAGE	119,436	0.263	0.239	0.044	0.216	0.425
log(1 + *LEVERAGE*)	119,436	0.217	0.181	0.044	0.195	0.354
REG	119,436	0.056	0.230	0.000	0.000	0.000
NIND	119,436	255.695	216.608	80.250	203.000	387.000
log(*NIND*)	119,436	5.119	1.015	4.390	5.310	5.960
NREV	41,312	33.903	42.015	6.000	17.667	44.600
log(1 + *NREV*)	41,312	2.856	1.277	1.946	2.927	3.820
ΔINST	41,312	0.133	0.147	0.055	0.093	0.160
log(1 + *ΔINST*)	41,312	0.118	0.107	0.053	0.089	0.148
TRADES	41,312	0.033	0.106	0.002	0.006	0.020
log(1 + *TRADES*)	41,312	0.029	0.079	0.002	0.006	0.020

See "Appendix" for variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles of the sample distribution the estimations of Eq. 1 is 0.760 (0.807), indicating a relatively weak association between firm-level earnings and the weighted average of market and industry earnings.[28] However, we note that the standard deviation of *UNEXPLAINED* (0.192) is large compared to the median. This statistic indicates that our sample exhibits considerable cross-sectional variation in the degree of earnings noncommonality. Similar conclusions can be drawn from the summary statistics for *NONCOMMON* (the log transformation of *UNEXPLAINED*). Our summary statistics for the reduced sample to be used in supplemental tests of returns noncommonality are similar. Specifically, we find that the mean (median) of *UNEXPLAINED_RET* is 0.786 (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 *INTANGINT* is 0.121 (0.052), indicating that, on average, intangible assets comprise about 12% 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 *RDINT* is 0.070 compared with the mean values of 0.011 and 0.040 for *SEPRBLINT* and *GDWLINT*, respectively. These differences are significant at the 1% level.

With respect to our control variables, we find that the mean (median) of the average market value of equity (*MVE*) is $855.3 million ($87.4 million), while the mean (median) of average total recognized assets (*ASSETS*) is $1.2 billion ($98.2 million). 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 *INTANGINT*, thus providing preliminary evidence that intangible investment influences earnings noncommonality. The Spearman correlations for the separate classes of intangibles indicate that *NONCOMMON* is positively associated with *SEPRBLINT* and *RDINT* but not significantly associated with *GDWLINT*. Moreover, the positive correlation between *NONCOMMON* and the market-to-book ratio (*MB*) suggests that other unrecognized intangibles may have a positive incremental effect on earnings noncommonality. Finally, we note that the signs of the correlations between *NONCOMMON* and our control variables are consistent with the predictions discussed previously in Sect. 3.2.

[28] 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 (2010) report a mean earnings noncommonality measure of 71% for a smaller sample of firms.

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**	**−0.05**	**0.05**	**0.02**	**−0.01**	0.00	**0.02**	**0.02**	**0.03**	**0.02**	0.00	**0.03**	**−0.11**	**−0.03**	**0.02**
(2) *NONCOMMON_RET*	**0.11**		**−0.10**	**−0.46**	**−0.19**	**0.10**	**0.14**	**0.00**	**−0.02**	**−0.09**	**0.01**	**0.04**	**0.03**	**0.05**	**−0.01**	**−0.48**	**0.01**	**0.14**
(3) *log(MB)*	0.00	**−0.11**		**0.20**	**−0.05**	**0.26**	**0.13**	**−0.08**	**−0.11**	**−0.10**	**0.23**	**0.34**	**0.10**	**0.05**	**0.35**	**0.14**	**−0.12**	**−0.03**
(4) *log(MVE)*	**−0.11**	**−0.47**	**0.22**		**0.39**	**−0.25**	**−0.29**	**−0.16**	**0.11**	**0.11**	0.00	**0.06**	**0.07**	**0.16**	**−0.05**	**0.74**	**0.16**	**−0.17**
(5) *MKTSHARE*	**−0.09**	**−0.29**	**−0.21**	**0.60**		**−0.13**	**−0.21**	**0.20**	**0.16**	**−0.03**	**−0.39**	**−0.09**	**−0.01**	**0.06**	**−0.15**	**0.31**	**0.10**	**−0.06**
(6) *STDROA*	**0.08**	**0.17**	**0.27**	**−0.41**	**−0.50**		**0.16**	**−0.01**	**−0.16**	**−0.08**	**0.13**	**0.19**	**0.07**	**0.02**	**0.19**	**−0.17**	**−0.13**	**0.06**
(7) *log*(1 + *DIVERS*)	**0.01**	**0.12**	**0.13**	**−0.26**	**−0.30**	**0.23**		**0.04**	**−0.16**	**−0.04**	**0.08**	**0.04**	**−0.02**	**−0.13**	**0.14**	**−0.17**	**−0.12**	**0.06**
(8) *log*(1 + *HERF*)	**−0.02**	0.01	**−0.10**	**−0.21**	**0.23**	**0.03**	**0.06**		**0.03**	**−0.11**	**−0.43**	**−0.19**	**−0.06**	**−0.03**	**−0.20**	**−0.05**	**0.03**	**0.04**
(9) *log*(1 + *LEVERAGE*)	**−0.01**	**−0.03**	**−0.16**	**0.13**	**0.37**	**−0.25**	**−0.20**	**0.04**		**0.15**	**−0.23**	**−0.19**	**0.04**	**0.09**	**−0.33**	**0.03**	**0.09**	**0.04**
(10) *REG*	**0.02**	**−0.09**	**−0.11**	**0.11**	**0.05**	**−0.17**	**−0.06**	**−0.24**	**0.16**		**0.02**	**−0.15**	**−0.03**	**−0.06**	**−0.13**	**0.02**	**0.04**	**−0.04**
(11) *log(NIND)*	**0.03**	**0.03**	**0.26**	0.00	**−0.56**	**0.21**	**0.09**	**−0.51**	**−0.26**	**−0.02**		**0.39**	**0.04**	**0.01**	**0.47**	**−0.06**	**−0.14**	**−0.05**
(12) *log*(1 + *INTANGINT*)	**0.03**	**0.05**	**0.35**	**0.08**	**−0.25**	**0.25**	**−0.01**	**−0.21**	**−0.21**	**−0.19**	**0.43**		**0.39**	**0.52**	**0.73**	**0.02**	**−0.13**	**−0.03**
(13) *log*(1 + *SEPRBLINT*)	**0.02**	**0.04**	**0.17**	**0.14**	**−0.03**	**0.07**	**−0.09**	**−0.12**	**−0.02**	**−0.08**	**0.10**	**0.45**		**0.22**	0.00	**0.04**	**−0.02**	**0.02**
(14) *log*(1 + *GDWLINT*)	0.00	**0.05**	**0.09**	**0.21**	**0.15**	**−0.02**	**−0.19**	**−0.03**	**0.08**	**−0.09**	**0.04**	**0.51**	**0.42**		**−0.10**	**0.09**	**0.01**	**0.03**
(15) *log*(1 + *RDINT*)	**0.02**	**−0.02**	**0.32**	**−0.01**	**−0.38**	**0.25**	**0.07**	**−0.25**	**−0.33**	**−0.18**	**0.55**	**0.70**	**0.13**	0.00		**−0.05**	**−0.17**	**−0.07**
(16) *log*(1 + *NREV*)	**−0.11**	**−0.50**	**0.18**	**0.75**	**0.47**	**−0.21**	**−0.16**	**−0.03**	**0.06**	**0.02**	**−0.05**	**0.05**	**0.09**	**0.13**	0.00		**0.05**	**−0.14**
(17) *log*(1 + *ΔINST*)	**−0.05**	**−0.01**	**−0.15**	**0.28**	**0.35**	**−0.34**	**−0.15**	**0.02**	**0.15**	**0.06**	**−0.19**	**−0.17**	**−0.06**	**0.02**	**−0.21**	**0.07**		**0.16**
(18) *log*(1 + *ΔTRADES*)	**0.03**	**0.31**	**−0.01**	**−0.37**	**−0.23**	**0.17**	**0.16**	**0.11**	**−0.05**	**−0.12**	**−0.04**	**−0.02**	**−0.01**	**0.01**	**−0.06**	**−0.32**	**0.09**	

See "Appendix" 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

5 Empirical results and robustness tests

5.1 Empirical results

5.1.1 *Do intangible investments affect the degree of earnings noncommonality (RQ1)?*

Columns 1–3 of Table 4 present the results of regressing *NONCOMMON* on *INTANGINT* as well as various control variables. To control for heteroskedasticity and unobserved within-firm and time-series correlation patterns, we base our inferences in this and all ensuing regressions on standard errors clustered by firm and calendar year (Petersen 2009). This two-way clustering approach also corrects for serial correlation that may arise from the use of overlapping rolling windows to estimate *NONCOMMON*. As noted earlier, we log transform several of the regression variables to control for skewness in the data distributions.

The estimated coefficient on *INTANGINT* is significantly positive ($\beta_1 = 0.362$; $p < 0.01$), suggesting that investment in intangible assets has a positive impact on the degree of earnings noncommonality. We also find a significantly positive association between *NONCOMMON* and the market-to-book ratio (*MB*; $\beta_2 = 0.039$, $p < 0.01$), indicating that other unrecognized intangible assets (those intangibles not captured by *INTANGINT*) have a positive incremental effect on the extent of earnings noncommonality. 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-goods view—is most descriptive of our sample. To gauge the economic significance of these results, we note that the estimated coefficient for *INTANGINT* indicates that, for every 10% increase in the sum of one plus the intangible intensity ratio, there is a 3.5% increase in our earnings noncommonality measure (*NONCOMMON*).[29]

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* suggests that less diversified firms tend to have a lower degree of earnings noncommonality. Consistent with our predictions, the significantly positive coefficient on *STDROA* indicate that firms with more volatile earnings have less comovement in their earnings streams. Contrary to expectations, we find that firms

[29] When the dependent and independent variables are both log transformed, the estimated coefficients can be interpreted in terms of percent change or elasticity (Wooldridge 2002). Therefore, from Table 4, the estimated coefficient of 0.362 for $log(1 + INTANGINT)$ represents a 3.5% increase for every 10% increase in $(1 + INTANGINT)$, i.e., $1.10^{0.362} = 1.0351$.

Table 4 Tests of the association between intangible intensity and earnings noncommonality

Dependent variable: *NONCOMMON*

Variable	(1) Coefficient estimate	(2) *t*-Statistic	(3) *p*-Value	(4) Coefficient estimate	(5) *t*-Statistic	(6) *p*-Value
Intercept	1.969	17.11	<0.01	1.957	16.11	<0.01
log(1 + *INTANGINT*)	0.362	3.80	<0.01	–	–	–
log(1 + *SEPRBLINT*)	–	–	–	1.021	3.73	<0.01
log(1 + *GDWLINT*)	–	–	–	0.287	1.86	0.06
log(1 + *RDINT*)	–	–	–	0.285	2.65	<0.01
log(*MB*)	0.039	3.40	<0.01	0.040	3.50	<0.01
log(*MVE*)	−0.082	−14.01	<0.01	−0.083	−13.99	<0.01
MKTSHARE	0.199	0.49	0.63	0.251	0.61	0.54
STDROA	0.462	3.16	<0.01	0.453	3.13	<0.01
log(1 + *DIVERS*)	−0.216	−2.24	0.03	−0.212	−2.10	0.04
log(1 + *HERF*)	−0.266	−1.45	0.15	−0.257	−1.41	0.16
log(1 + *LEVERAGE)*	0.107	2.05	0.04	0.097	1.78	0.08
REG	0.253	4.00	<0.01	0.253	4.00	<0.01
log(*NIND*)	0.004	0.24	0.81	0.007	0.42	0.68
Adjusted R^2	1.53%			1.56%		
Number of observations	119,436			119,436		

See "Appendix" 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

operating in regulated industries (*REG*) tend to have less earnings commonality, as evidenced by the positive association between *NONCOMMON* and *REG*.[30,31]

Taken together, the results for RQ1 suggest that investment in intangible resources is an important factor that drives the extent of noncommonality in firm-level earnings, consistent with the resource-based view. Moreover, the estimated

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

[31] We acknowledge the modest explanatory power of our earnings noncommonality regression despite the fact that we have included all determinants of which we are aware based on the existing literature. However, given that research on the determinants of earnings noncommonality is in its infancy, it is likely that our list of determinants is not comprehensive. The low explanatory power of our regression model could also reflect that our earnings noncommonality measure captures correlations in realized performance over short horizons whereas the differentiating or commonality-inducing effects of intangibles likely take place over longer horizons. To address this issue, we replicate our regressions using a stock return-based measure of noncommonality, which captures not only realized performance but anticipated future performance (see Sect. 5.2.1 for further details). Consistent with prior research (e.g., Piotroski and Roulstone 2004), we find that the R^2s from the returns-based models are substantially higher (between 25 and 30%), indicating that a noncommonality measure that incorporates both short- and anticipated long-term effects leads to regression models with better explanatory power.

signs of our control variables are largely consistent with prior research (Morck et al. 2000; Piotroski and Roulstone 2004) and thus further validate our results.

5.1.2 Do the various classes of recognized and unrecognized intangibles differentially affect the degree of earnings noncommonality (RQ2)?

Our next research question (RQ2) addresses the differential impact of various classes of recognized and unrecognized intangibles on earnings noncommonality. Columns 4–6 of Table 4 present the results of regressing *NONCOMMON* on the average asset intensity level for the following classes of intangibles: separable recognized intangibles (*SEPRBLINT*), goodwill (*GDWLINT*), and R&D capital (*RDINT*) as well as the various control variables. The estimated coefficients for *SEPRBLINT* ($\delta_1 = 1.021$; $p < 0.01$), *GDWLINT* ($\delta_2 = 0.287$; $p = 0.06$), and *RDINT* ($\delta_3 = 0.285$; $p < 0.01$) collectively suggest that both recognized and unrecognized intangibles contribute significantly to earnings noncommonality. Notably, we find that the estimated coefficient for *SEPRBLINT* is significantly higher than each of the estimated coefficients for *GDWLINT* and *RDINT*. (*F*-tests of these differences in the coefficients are significant at less than the 5% level.) To gauge the economic significance of these results, we note that the estimated coefficient for *SEPRBLINT* indicates that, for every 10% increase in the sum of one plus the separable intangible intensity ratio, there is a 10.22% increase in *NONCOMMON*. In contrast, the estimated coefficients for *GDWLINT* and *RDINT* indicate an increase of 2.77 and 2.75%, respectively, in *NONCOMMON* for every 10% increase in the sum of one plus *GDWLINT* and the sum of one plus *RDINT*. These results suggest that separable recognized intangibles have a greater impact on earnings noncommonality than goodwill and R&D capital, consistent with the conjecture that intangible assets arising from contractual or legal property rights are more excludable and thus less susceptible to expropriation by 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 affect the relation between intangible investment and earnings noncommonality (RQ3)?

We provide direct evidence on the incremental effect of enforceable property rights on the association between intangible investments and earnings noncommonality (RQ3). Table 5 presents the regression analysis of RQ3 for the subsample of 51,401 firm-years in the manufacturing industry for which the *LEGALRIGHTS* variable is available.[32] The results indicate that the interaction of *RDINT* with *LEGALRIGHTS* is significantly positive ($\gamma_4 = 0.510$; $p = 0.02$), suggesting a greater positive effect of *RDINT* on *NONCOMMON* for those industries with strong legal property rights

[32] We do not interact *LEGALRIGHTS* with *SEPRBLINT* or *GDWLINT* since the survey data relates only to the appropriability conditions surrounding R&D investments. However, in robustness tests, our inferences are unchanged when we interact *LEGALRIGHTS* with both *SEPRBLINT* and *GDWLINT*.

Table 5 Impact of appropriability conditions on the association between R&D intensity and earnings noncommonality

Dependent variable: *NONCOMMON*

Variable	Coefficient estimate	*t*-Statistic	*p*-Value
Intercept	1.967	10.17	<0.01
log(1 + *SEPRBLINT*)	1.038	2.68	<0.01
log(1 + *GDWLINT*)	0.518	2.10	0.04
log(1 + *RDINT*)	0.235	1.36	0.17
log(1 + *RDINT*) × *LEGALRIGHTS*	0.510	2.35	0.02
LEGALRIGHTS	−0.140	−3.99	<0.01
log(*MB*)	0.023	1.53	0.13
log(*MVE*)	−0.091	−10.14	<0.01
MKTSHARE	0.360	0.37	0.71
STDROA	0.977	5.29	<0.01
log(1 + *DIVERS*)	−0.166	−1.42	0.16
log(1 + *HERF*)	−0.624	−1.00	0.32
log(1 + *LEVERAGE*)	−0.018	−0.25	0.80
log(*NIND*)	0.018	0.66	0.51
Adjusted R^2	2.39%		
Number of Observations	51,401		

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" 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

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 noncommonality.

5.2 Extensions and robustness tests

5.2.1 Intangible investment and noncommonality in stock returns

We focus on earnings noncommonality in our primary tests because this measure most closely captures correlation in firm fundamentals, which is our construct of interest. By contrast, noncommonality 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 noncommonality in stock returns because this measure potentially yields valuable insights. Specifically, given that stock returns presumably reflect economically important phenomena, tests using noncommonality 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, the analysis of stock return noncommonality provides 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 may partly reflect differences in accounting treatment of economic events across firms (De Franco et al. 2011; Durnev et al. 2003; Elgers et al. 2004), returns-based measures have no such limitation.

As described in the appendix, we construct our stock return noncommonality measure (*NONCOMMON_RET*) in a manner analogous to earnings noncommonality (*NONCOMMON*). We re-estimate our results using extended versions of our regressions, where we replace the dependent variable *NONCOMMON* with *NONCOMMON_RET* and include several control variables suggested by Piotroski and Roulstone (2004). These additional variables (see the appendix) include *NONCOMMON* as well as several variables related to the information- and

Table 6 Tests of the association between intangible intensity and returns noncommonality

Dependent variable: *NONCOMMON_RET*

Variable	(1) Coefficient estimate	(2) *t*-Statistic	(3) *p*-Value	(4) Coefficient estimate	(5) *t*-Statistic	(6) *p*-Value
Intercept	3.364	12.47	<0.01	3.147	12.17	<0.01
log(1 + *INTANGINT*)	0.527	2.38	0.02	–	–	–
log(1 + *SEPRBLINT*)	–	–	–	1.137	2.90	<0.01
log(1 + *GDWLINT*)	–	–	–	1.514	5.21	<0.01
log(1 + *RDINT*)	–	–	–	−0.818	−2.86	<0.01
log(*MB*)	0.016	0.54	0.59	0.060	1.93	0.05
log(*MVE*)	−0.154	−4.55	<0.01	−0.177	−5.43	<0.01
MKTSHARE	−0.333	−0.59	0.56	0.358	0.66	0.51
STDROA	−0.110	−0.21	0.84	−0.048	−0.09	0.93
log(1 + *DIVERS*)	0.307	1.67	0.09	0.443	2.61	<0.01
log(1 + *HERF*)	−0.951	-4.16	<0.01	−1.025	−4.36	<0.01
log(1 + *LEVERAGE*)	0.265	3.07	<0.01	0.047	0.64	0.524
REGULATED	−0.377	−6.03	<0.01	−0.377	−6.19	<0.01
log(*NIND*)	−0.073	−3.74	<0.01	−0.014	−0.90	0.37
NONCOMMON	0.047	6.86	<0.01	0.049	7.12	<0.01
log(1 + *NREV*)	−0.282	−9.95	<0.01	−0.276	−10.24	<0.01
log(1 + *ΔINST*)	0.192	0.99	0.32	0.091	0.48	0.63
log(1 + *TRADES*)	0.881	4.43	<0.01	0.757	3.78	<0.01
Adjusted R^2	26.75%			28.12%		
Number of observations	41,312			41,312		

See "Appendix" 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 trading-related activities of financial analysts and institutional investors including: forecast revision frequency (*NREV*), share turnover by institutional investors (Δ*INST*), and the net share purchase activity by insiders (*TRADES*). Due to additional data restrictions, our sample declines to 41,312 for the analysis of RQ1 and RQ2 and to 19,343 for the analysis of RQ3.

The results presented in Table 6 are largely consistent with our earnings noncommonality tests. That is, we find that total intangible intensity is positively related to noncommonality in returns ($p = 0.02$) and that goodwill and separable intangible assets are also positively related to noncommonality in stock returns ($p < 0.01$).

In contrast to the earnings-based tests, however, we find that R&D is negatively related to returns noncommonality. This result is consistent with the extensive literature on R&D spillovers. The differing effects of R&D for the earnings-based

Table 7 Impact of appropriability conditions on the association between R&D intensity and returns noncommonality

Dependent variable: *NONCOMMON_RET*

Variable	Coefficient estimate	*t*-Statistic	*p*-Value
Intercept	2.471	7.66	<0.01
log(1 + *SEPRBLINT*)	0.926	1.57	0.12
log(1 + *GDWLINT*)	1.104	2.68	<0.01
log(1 + *RDINT*)	−1.689	−3.63	<0.01
log(1 + *RDINT*) × *LEGALRIGHTS*	0.864	2.86	<0.01
LEGALRIGHTS	0.072	1.42	0.16
log(*MB*)	0.053	1.33	0.18
log(*MVE*)	−0.117	−3.39	<0.01
MKTSHARE	−1.033	−1.13	0.26
STDROA	0.007	0.01	0.99
log(1 + *DIVERS*)	0.594	3.04	<0.01
log(1 + *HERF*)	−0.888	−1.22	0.22
log(1 + *LEVERAGE*)	0.309	2.71	<0.01
log(*NIND*)	0.058	2.18	0.03
NONCOMMON	0.035	4.13	<0.01
log(1 + *NREV*)	−0.321	−9.20	<0.01
log(1 + *ΔINST*)	−0.051	−0.18	0.86
log(1 + *TRADES*)	1.106	3.64	<0.01
Adjusted R^2	27.73%		
Number of observations	19,343		

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" 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 versus the returns-based measures of noncommonality 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 captures not only associations between realized performances over short horizons but also associations between anticipated long-run performances. 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.

Lastly, in Table 7, the positive coefficient on the interaction between *RDINT* and *LEGALRIGHTS* ($p < 0.01$) is consistent with the analogous earnings-based tests presented in Table 5. This result indicates that the existence of effective legal property rights is instrumental in the extent to which R&D investment contributes to noncommonalities in fundamental performance.

5.2.2 Earnings forecasting and intangibles-driven noncommonality in earnings

An implication of our findings is that intangible investment affects the relative importance of market and industry information when forecasting a 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 an indicator variable corresponding to *RNOA* that is below the median, and (3) predicted sales growth from a first-order autoregressive sales growth forecast model.

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 two-digit SIC code as the firm for which a forecast is being generated. 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 mean and median 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 mean forecast accuracy improvements from using the market-wide model over a random walk expectation ($p < 0.01$) but no significant forecast accuracy improvements from using the industry-based model over the market-wide model ($p = 0.73$). Fairfield et al. (2009) attribute the latter finding to unspecified heterogeneity among firms in the same industry, which hinders the ability of the

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	<0.01	0.000	0.73
Median improvement	0.001	<0.01	0.000	0.27
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	<0.01	0.003	14.09	<0.01
log(1 + *INTANGINT*)	−0.002	−1.59	0.11	–	–	–
log(1 + *SEPRBLINT*)	–	–	–	−0.005	−1.87	0.06
log(1 + *GDWLINT*)	–	–	–	−0.006	−3.05	<0.01
log(1 + *RDINT*)	–	–	–	0.004	2.05	0.04
Adjusted R^2	0.00%			0.02%		
Number of observations	87,865			87,865		

Panel C: Dependent variable: *IMPROVE_IND*

Variable	Coefficient estimate	*t*-Statistic	*p*-Value	Coefficient estimate	*t*-Statistic	*p*-Value
Intercept	−0.000	−1.46	0.14	−0.000	−1.78	0.07
log(1 + *INTANGINT*)	0.001	1.85	0.07	–	–	–
log(1 + *SEPRBLINT*)	–	–	–	0.001	1.49	0.14
log(1 + *GDWLINT*)	–	–	–	−0.004	−5.18	<0.01
log(1 + *RDINT*)	–	–	–	0.005	6.79	<0.01
Adjusted R^2	0.00%			0.08%		
Number of observations	87,865			87,865		

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" for all other variable definitions. The reported *p*-values are two-tailed and are based on robust standard errors clustered by firm

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 the relation between *INTANGINT* and forecast accuracy improvements is not statistically significant at conventional levels, we find that both *SEPRBLINT* and *GDWLINT* significantly reduce the improvements generated by the market-wide model ($p = 0.06$ and

<0.01, 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 *RDINT* increases the forecast improvements generated by the market-wide model ($p = 0.04$), 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 noncommonality 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 *INTANGINT* and forecast accuracy improvements ($p = 0.07$). This relation appears to be attributable to the positive impact of *RDINT* ($p < 0.01$) that offsets the negative impact of *GDWLINT* ($p < 0.01$). 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 Examination of firm-specific and industry-driven intangible investment

Past research documents a strong industry component to firms' intangible investment as firms are partly motivated to undertake intangible investment in order to keep pace with their industry (for example, Mauri and Michaels 1998; Litov et al. 2010). Therefore, we decompose our intangible intensity measures into a firm-specific component and an industry component and examine the extent to which these two components influence our overall results. Following Barth et al. (2001), we define the industry component for each intangible intensity measure as the average of that measure for all firms in the same two-digit SIC code. We define the firm-specific component as the firm's intangible intensity measure less the industry component. We then replicate our tests of RQ1 through RQ3 after replacing the overall intangible intensity measures with their firm-specific and industry components. In untabulated analyses, we find that both components of intangible investment contribute to our overall results.

5.2.4 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 noncommonality measure (*NONCOMMON*), we recalculate *NONCOMMON* using ROA based on earnings before interest, taxes, depreciation, and amortization (adjusted for R&D amortization and capitalization) based on Durnev et al.'s (2003) insight that these components of earnings are the most vulnerable to differences in accounting practices. Second, we re-estimate all our regressions after excluding all observations with zero values for *INTANGINT*. Finally, to further address potential serial correlation due to the use of overlapping windows in the estimation of *NONCOMMON*, we replicate our tests using subsamples of firm-year observations with completely non-overlapping data.[33] Our inferences are robust to these additional procedures.

6 Conclusion

For a sample of US firms over the 1980–2006 period, we document a positive relation between a firm's intangible asset intensity and earnings noncommonality, consistent with the resource-based view. We find that separable recognized intangible assets, goodwill, and R&D all contribute positively to earnings noncommonality. We also find that R&D investment engenders even greater earnings noncommonalities for those industries where patents and other legal mechanisms are most effective in protecting R&D innovations. This evidence suggests that appropriability conditions influence the extent to which intangible investment contributes to economic differentiation, as measured by earnings noncommonality. In addition, separable recognized intangible assets contribute more to earnings noncommonality than either goodwill or R&D investment. This result may reflect the fact that separable recognized intangibles arise from contractual or legal rights and thus are less susceptible to expropriation by rival firms.

We document similar associations between intangible intensity and stock return noncommonality, with the exception of R&D, which is negatively related to returns noncommonality. This result is consistent with the extensive R&D spillover literature and suggests that, even though R&D allows firms to economically differentiate themselves in the short run (as demonstrated by our earnings noncommonality tests), investors anticipate R&D to engender long-run commonalities among firms. Also, we document that the intensity and type of firms' intangible investment affects the performance of the market- and industry-based profitability forecast models examined by Fairfield et al. (2009), demonstrating the implications of our results for the relative importance of market and industry information in forecasting firm-level 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 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. Our evidence that

[33] Specifically, we again retain the fourth calendar quarter of each firm-year and then form separate non-overlapping subsamples using observations that are 5 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.

intangible investments contribute positively to earnings noncommonality suggests that intangible assets do not act primarily as pure public goods and thus may alleviate concerns of 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 noncommonality, in particular R&D capital, depends not only on their fundamental properties but also on the strength of mechanisms used to protect these assets.

Acknowledgments We thank Bill Baber, Ted Christensen, David Erkens, Jennifer Francis, Bjorn Jorgensen, Partha Mohanram, Tatiana Melguizo, Darren Roulstone (discussant), Stephen Ryan (editor), two anonymous referees, Tatiana Sandino, and workshop participants at Columbia Business School, George Mason University, Georgetown University, the 2010 *Review of Accounting Studies* Conference at the University of Notre Dame, and the Information, Markets, and Organization Conference at Harvard Business School for helpful comments and suggestions. We thank Marquita Barnes for excellent research assistance.

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 (*RDCAP*) as of the beginning of calendar quarter *t*. *RDCAP* 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 those in the same two-digit SIC code as 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 those in the same two-digit SIC code as 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 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.

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

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);
$INDRET_{i,t}$ = 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).

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

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

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

where *INTANG* = (*SEPRBL* + *GDWL* + *RDCAP*), and *N* = the number of nonmissing observations over the 20 quarter period. *SEPRBL* is the amount of separable recognized intangible assets (excluding goodwill, data item INTANQ); *GDWL* is the amount of recognized goodwill (data item GDWLQ); *RDCAP* is the estimated unamortized cost of R&D investment; *ASSETS* is total recognized assets (data item ATQ).

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

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

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

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

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

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

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

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

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

STDROA = the standard deviation of return on assets (*ROA*) measured over the number of quarters with nonmissing 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 the firm, where the average is measured using the number of quarters with nonmissing 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 nonmissing 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 the sum of long-term debt (data item DLTTQ) and book value of equity (data item CEQQ) of the firm, where the average is calculated over the number of quarters with nonmissing 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 nonmissing data (*N*) comprising with the estimation period used to calculate *UNEXPLAINED* and *NONCOMMON*.

REG = 1 if the firm 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 nonmissing data (*N*) comprising the estimation period used to calculate *UNEXPLAINED* and *NONCOMMON*.

ΔINST = 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 nonmissing 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 nonmissing data (*N*) comprising the estimation period used to calculate *UNEXPLAINED* and *NONCOMMON*.

References

Arrow, K. (1962). Economic welfare and the allocation of resources for invention. In R. Nelson (Ed.), *The rate and direction of inventive activity: Economic and social factors*. New York, NY: National Bureau of Economic Research Special Conference Series.

Ball, R., & Brown, P. (1967). Some preliminary findings on the association between the earnings of a firm, its industry, and the economy. *Journal of Accounting Research, 5*, 55–77.

Ball, R., Sadka, G., & Sadka, R. (2009). Aggregate earnings and asset prices. *Journal of Accounting Research, 47*(5), 1097–1133.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99–120.

Barth, M., & Kasznik, R. (1999). Share repurchases and intangible assets. *Journal of Accounting and Economics, 28*(2), 211–241.

Barth, M., Kasznik, R., & McNichols, M. (2001). Analyst coverage and intangible assets. *Journal of Accounting Research, 39*(1), 1–34.

Basu, S., & Waymire, G. (2008). Has the importance of intangibles really grown? And if so, why? *Accounting and Business Research, 38*(3), 171–190.

Beaver, W., Kettler, P., & Scholes, M. (1970). The association between market determined and accounting determined risk measures. *The Accounting Review, 45*(4), 654–682.

Bhide, A. (2000). *The origin and evolution of new businesses*. New York: Oxford University Press.

Bradley, M., Jarrell, G., & Kim, E. (1984). On the existence of an optimal capital structure: Theory and evidence. *Journal of Finance, 39*(3), 857–878.

Cockburn, I., & Griliches, Z. (1988). The estimation and measurement of spillover effects of R&D investment: Industry effects and appropriability measures in the stock market's valuation of R&D and patents. *American Economic Review, 78*(2), 419–423.

Cohen, W., Goto, A., Nagata, A., Nelson, R., & Walsh, J. (2002). R&D spillovers, patents, and the incentives to innovate in Japan and the United States. *Research Policy, 31*(8–9), 1349–1367.

Cohen, W., & Levin, R. (1989). Empirical studies of innovation and market structure. In R. Schmalensee & R. Willig (Eds.), *Handbook of Industrial Organization*. Amsterdam: North Holland.

Cohen, W., & Levinthal, D. (1989). Innovation and learning: The two faces of R&D. *The Economic Journal, 99*(397), 569–596.

Cohen, W., Nelson, R., & Walsh, J. (2000). *Protecting their intellectual assets: Appropriability conditions and why U.S. manufacturing firms patent (or not)*. NBER Working Paper No. 7552.

Cubbin, J., & Geroski, P. (1987). The convergence of profits in the long run: Inter-firm and inter-industry comparisons. *Journal of Industrial Economics, 35*(4), 427–442.

Cyert, R. (1967). Discussion of some preliminary findings on the association between the earnings of a firm, its industry, and the economy. *Journal of Accounting Research, 5*, 78–80.

Davis, L. (2001). R&D investments, information, and strategy. *Technology Analysis & Strategic Management, 13*(3), 325–342.

De Franco, G., Kothari, S.P., & Verdi, R. (2011). The benefits of financial statement comparability. *Journal of Accounting Research* (forthcoming).

Dierickx, I., & Cool, K. (1989). Asset stock accumulation and sustainability of competitive advantage. *Management Science, 35*(12), 1504–1511.
Dosi, G. (1988). Sources, procedures, and microeconomic effects of innovation. *Journal of Economic Literature, 26*(3), 1120–1171.
Durnev, A., Morck, R., & Yeung, B. (2004). Value-enhancing capital budgeting and firm-specific stock return variation. *Journal of Finance, 59*(1), 65–105.
Durnev, A., Morck, R., Yeung, B., & Zarowin, P. (2003). Does greater firm-specific return variation mean more or less informed stock pricing? *Journal of Accounting Research, 41*(5), 797–836.
Elgers, P., Porter, S., & Xu, L. (2004). *Birds of a feather: Do co-movements in accounting fundamentals help to explain commonalities in securities returns?* Working paper, University of Massachusetts (Amherst).
Engelberg, J., Ozoguz, A., & Wang, S. (2009). *Know thy neighbor: Industry clusters, information spillovers, and market efficiency*. Working paper, University of North Carolina (Chapel Hill).
Erkens, D. (2010). *The influence of property rights on the relation between research and development investments and equity-based compensation*. Working paper, University of Southern California.
Fairfield, P., Ramnath, S., & Yohn, T. (2009). Do industry-level analyses improve forecasts of financial performance? *Journal of Accounting Research, 47*(1), 147–178.
Financial Accounting Standards Board (FASB). (1985). *Statement of financial accounting concepts No. 6*. Stamford: FASB.
Gilson, R. J. (1999). The legal infrastructure of high technology industrial districts: Silicon Valley, Route 128, and covenants not to compete. *New York University Law Review, 74*(3), 575–629.
Gonedes, N. (1973). Properties of accounting numbers: Models and tests. *Journal of Accounting Research, 11*(2), 212–237.
Gong, G., Li, L., & Zhou, L. (2009). *Earnings non-synchronicity and voluntary disclosure*. Working paper, Pennsylvania State University.
Hall, R. (1993). A framework linking intangible resources and capabilities to sustainable competitive advantage. *Strategic Management Journal, 14*(8), 607–618.
Hall, B. (2002). The financing of research and development. *Oxford Review of Economic Policy, 18*(1), 35–51.
Horstmann, I., MacDonald, G., & Slivinski, A. (1985). Patents as information transfer mechanisms: To patent or (maybe) not to patent. *Journal of Political Economy, 93*(5), 837–858.
Itami, H. (1987). *Mobilizing invisible assets*. Cambridge: Harvard University Press.
Jaffe, A. (1986). Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value. *The American Economic Review, 76*(5), 984–1001.
Jin, L., & Myers, S. (2006). R^2 around the world: New theory and new tests. *Journal of Financial Economics, 79*(2), 257–292.
Kahaner, L. (1997). *Competitive intelligence: How to gather, analyze, and use information to move your business to the top*. New York: Simon and Schuster.
Kimbrough, M., & Wang, I. (2010). *Evidence on investors' assessment of the plausibility of seemingly self-serving attributions of earnings performance*. Working paper, University of Maryland.
Kini, O., Mian, S., Rebello, M., & Venkateswaran, A. (2009). On the structure of analyst research portfolios and forecast accuracy. *Journal of Accounting Research, 47*(4), 867–909.
Kothari, S., Laguerre, T., & Leone, A. (2002). Capitalization versus expensing: Evidence on the uncertainty of future earnings from capital expenditures versus R&D outlays. *Review of Accounting Studies, 7*(4), 355–382.
Lavelle, L. (2001). *The case of the corporate spy: In a recession, competitive intelligence can pay off big*. Business Week (November 26).
Lev, B. (2001). *Intangibles: Management, measurement, and reporting*. Washington, DC: Brookings Institution Press.
Lev, B., & Sougiannis, T. (1996). The capitalization, amortization, and value-relevance of R&D. *Journal of Accounting and Economics, 21*(1), 107–138.
Levin, R., Klevorick, A., Nelson, R., & Winter, S. (1987). Appropriating the returns from industrial research and development. *Brookings Papers on Economic Activity, 1987*(3), 783–819.
Lippman, S., & Rumelt, R. (1982). Uncertain imitability: An analysis of interfirm differences in efficiency under competition. *Bell Journal of Economics, 13*(2), 418–438.
Litov, L., Moreton, P., & Zenger, T. (2010). *Corporate strategy, analyst coverage, and the uniqueness paradox*. Working paper, Washington University at St. Louis.

Long, M., & Malitz, I. (1985). Investment patterns and financial leverage. In B. Friedman (Ed.), *Corporate capital structures in the United States* (pp. 325–351). Chicago: University of Chicago Press.

Magee, R. (1974). Industry-wide commonalities in earnings. *Journal of Accounting Research, 12*(2), 270–287.

Maines, L., Bartov, E., Fairfield, P., Hirst, D., Iannaconi, T., Mallett, R., Schrand, C., Skinner, D. (principal author), & Vincent, L. (2003). Implications of accounting research for the FASB's initiatives on disclosure of information about intangible assets. *Accounting Horizons*, 17(2), 175–185.

Mansfield, E. (1985). How rapidly does new industrial technology leak out? *Journal of Industrial Economics, 34*(2), 217–223.

Mansfield, E. (1986). Patents and innovation: An empirical study. *Management Science, 32*(2), 173–181.

Marx, M., Strumsky, D., & Fleming, L. (2009). Mobility, skills, and the Michigan non-compete experiment. *Management Science, 55*(6), 875–889.

Matolcsy, Z., & Wyatt, A. (2008). The association between technological conditions and the market value of equity. *The Accounting Review, 83*(2), 479–518.

Mauri, A., & Michaels, M. (1998). Firm and industry effects within strategic management: An empirical examination. *Strategic Management Journal, 19*(3), 211–219.

McGahan, A., & Porter, M. (1997). How much does industry matter, really? *Strategic Management Journal, 18*(Summer), 15–30.

McGahan, A., & Porter, M. (2002). What do we know about variance in accounting profitability? *Management Science, 48*(7), 834–851.

Moen, J. (2005). Is mobility of technical personnel a source of R&D spillovers? *Journal of Labor Economics, 23*(1), 81–114.

Morck, R., Yeung, B., & Yu, W. (2000). The information content of stock markets: Why do emerging markets have synchronous stock price movements? *Journal of Financial Economics, 58*(1–2), 215–260.

Nelson, R. (1991). Why do firms differ, and how does it matter? *Strategic Management Journal, 12*(Winter), 61–74.

Palepu, K., Healy, P., & Bernard, V. (2007). *Business analysis and valuation: Using financial statements* (4th Edition ed.). Mason: Thomson South-Western.

Peles, Y. (1970). Amortization of advertising expenditures in the financial statements. *Journal of Accounting Research, 8*(1), 128–137.

Petersen, M. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies, 22*(1), 435–480.

Piotroski, J., & Roulstone, D. (2004). The influence of analysts, institutional investors, and insiders on the incorporation of market, industry, and firm-specific information into stock prices. *The Accounting Review, 79*(4), 1119–1151.

Prescott, J., & Bhardwaj, G. (1995). Competitive intelligence practices: A survey. *Competitive Intelligence Review, 6*(2), 4–14.

Romer, P. (1990). Endogenous technological growth. *Journal of Political Economy, 98*(5), S71–S102.

Rumelt, R. (1984). Towards a strategic theory of the firm. In B. Lamb (Ed.), *Competitive strategic management*. Englewood Cliffs: Prentice Hall.

Rumelt, R. (1991). How much does industry matter? *Strategic Management Journal, 12*(3), 167–185.

Schmalensee, R. (1985). Do markets differ much? *American Economic Review, 75*(3), 341–351.

Shiller, R. (1989). Comovements in stock prices and comovements in dividends. *Journal of Finance, 44*(3), 719–730.

Skinner, D. (2008). Accounting for intangibles: A critical review of policy recommendations. *Accounting and Business Research, 38*(3), 191–204.

Teece, D. (1986). Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research Policy, 15*(6), 285–305.

Villalonga, B. (2004). Intangible resources, Tobin's Q, and sustainability of performance differences. *Journal of Economic Behavior & Organization, 54*(2), 205–230.

Von Hoffman, C. (1999). *Competitive intelligence: A primer*. Harvard Management Update, September 3–4.

Williams, T. (1967). Discussion of some preliminary findings on the association between the earnings of a firm, its industry, and the economy. *Journal of Accounting Research, 5*, 81–85.

Wooldridge, J. (2002). *Introductory econometrics: A modern approach*. Cincinnati: South-Western College Publishing.