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Why have measures of earnings quality changed over time? ☆

Anup Srivastava *

Accounting Information and Management Department, Kellogg School of Management, Northwestern University, 6220 Jacobs Center, 2001 Sheridan Road, Evanston, IL 60208-2001, USA

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ABSTRACT

The properties of earnings have changed dramatically over the past 40 years. Prior studies interpret this trend as a decline in earnings quality but disagree on whether it results from changes in the real economy or changes in accounting standards. I find that each new cohort of listed firms exhibits lower earnings quality than its predecessors, mainly because of higher intangible intensity. I conclude that the trend of decline in earnings quality is due more to changes in the sample of firms than to changes in generally accepted accounting principles (GAAP) or in the earnings quality of previously listed firms.

1. Introduction

The literature finds that over the past 40 years or so, there has been an increase in the volatility of earnings and a decrease in both the relevance of earnings and the degree of matching between concurrent revenues and expenses.[1] The literature interprets these changes as a decline in earnings quality (EQ). But there is disagreement about whether the decline is “due to changes in GAAP or due to real economic changes” (Collins et al., 1997, p. 65). I reexamine this question by using

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* Tel.: +1 847 467 6203.
E-mail address: anup-srivastava@kellogg.northwestern.edu

[1] See Collins et al. (1997), Lev and Zarowin (1999), Givoly and Hayn (2000) and Dichev and Tang (2008). The relevance of earnings is measured by the adjusted-R^2 of the regression of annual stock returns on the levels of, and changes in, annual earnings (Easton and Harris, 1991; Lev and Zarowin, 1999). The volatility of earnings is measured by the standard deviation of earnings over a rolling four-year window. Matching is measured by the coefficient on the current expenses in a regression of revenues on past, current, and future expenses (Dichev and Tang, 2008). Matching represents the contemporaneous revenue–expense correlation.

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more recent data than do most prior studies, allowing me to shed light on the issue in three ways. First, I show a strong negative correlation between intangible intensity and average EQ measures, i.e., volatility, relevance, and matching. (For ease of discussion, an increase in earnings volatility is viewed as a declining EQ measure.) Second, I show that successive cohorts of newly listed firms exhibit increasing intangible intensity and decreasing EQ measures. Third, I show that the progressive declines in EQ measures are largely the result of the assimilation of successive cohorts of newly listed firms into the firm population. Hence, I identify the "new-list" phenomenon as the biggest reason for the decline in average EQ measures over the study period of 1970 to 2009.

By the outset of the twenty-first century, the United States had moved from being primarily an industrial economy to becoming mainly a knowledge-based economy (Baumol and Schramm, 2010; Shapiro and Varian, 1998). As a result, U.S. firms have increased their investments in intangible capital such as innovation, advertising, information technology, human capital, and customer relations (Corrado and Hulten, 2010). Consistent with this trend, there has been a dramatic increase over time in U.S. firms' average intangible intensity as measured by research and development (R&D) expenses, market-to-book ratios, and selling, general, and administrative (SG&A) expenses (Francis and Schipper, 1999; Banker et al., 2011; Eisfeldt and Papanikolaou, 2013).

I hypothesize that increases in intangible intensity reduce earnings quality for several reasons. An intangible-intensive firm is likely to display high volatility in its revenues and cash flows because intangible investments carry higher uncertainty about future benefits than do tangible investments (Kothari et al., 2002). Furthermore, relative to material-intensive firms, intangible-intensive firms are more likely to have growth options, whose values and changes in values are typically not recognized in the balance sheet and income statement (Smith and Watts, 1992; Watts, 2003; Roychowdhury and Watts, 2007; Skinner, 2008). Similarly, firms generally expense their investments in internally generated intangibles as incurred, except for industry-specific practices (e.g., SOP 98-1 [AICPA 1998] for software firms). An immediate expensing of intangible investments, irrespective of when their associated benefits materialize, should increase the volatility in expenses and reduce the matching between concurrent revenues and expenses. The increased revenue and expense volatilities, compounded by the decline in matching, should increase the volatility in earnings. But volatile earnings are less informative for predicting a firm's future fundamentals (Dichev and Tang, 2009; Barton et al., 2010). Thus, intangible-intensive firms should display less earnings relevance. As expected, I find a strong and negative association between intangible intensity and average EQ measures (volatility, relevance, and matching).

I next examine whether the temporal trends in intangible intensity and EQ measures encompass all firms. I find that an increasing percentage of "new" firms, i.e., those listed after 1970 (Fama and French, 2004), enter knowledge-intensive industries such as business services, communications, pharmaceuticals, healthcare, and computers. These industries mainly transform "information from one pattern into another," unlike material-intensive industries that transform "matter and energy from one form into another" (Apte et al., 2008, p. 15). Thus, knowledge-intensive industries need a higher proportion of intangible inputs in their production functions than do material-intensive industries. Consistent with this idea, successive cohorts of new firms show increasing intangible intensity. In contrast, "seasoned" firms (those listed before 1970) continue to operate in material-intensive industries, such as textiles, utilities, aircraft, steel, and railroads. Following Fama and French (2004), these findings show that seasoned firms continue to pursue businesses that have reached the mature phases of their lifecycles (Anthony and Ramesh, 1992; Jovanovic and MacDonald, 1994).[2] In such phases, firms tend not to radically change their production functions unless breakthroughs in production technology occur (Hambrick, 1983; Chen et al., 2010). Consistent with this concept, increases in average intangible intensity over time mainly reflect the increasing intangible intensity of the successive cohorts of new firms rather than increasing intangible usage by seasoned firms.

In addition, I find that the average EQ measures of the firm population exhibit a declining trend. More important, successive cohorts of new firms display declining EQ measures despite controls for overall time trends. I investigate these trends by dividing the firm population into seasoned-firm and new-firm segments. The number of firms in the new-firm segment increases and its average EQ measures decline with the arrival of each new listing cohort. As a result, the average EQ measures of the new-firm segment decline more rapidly than those of the seasoned-firm segment. The average earnings relevance (the adjusted-R^2 of the regression of annual stock returns on levels of, and changes in, annual earnings) of the new-firm segment declines from 20.4% to just 2.6% from the period 1970–1974 to the period 2005–2009. This decline shows that the earnings of new firms no longer explain the variation in their stock returns in any economically significant way. In comparison, the average earnings relevance for seasoned firms declines less dramatically, from 20.1% to 14.4%. Further, for the new-firm segment, the average matching, measured by the concurrent revenue–expense association (Dichev and Tang, 2008), declines from 1.05 to just 0.59. This decline shows that a significant portion of the new firms' outlays are now expensed before recognition of the associated revenues. In comparison, the average revenue–expense matching of the seasoned-firm segment declines by much less, from 1.05 to 0.94. Similarly, the average earnings volatility of the new-firm segment increases more sharply. As a result, at the end of the study period, relative to the seasoned-firm segment, the new-firm segment's average earnings relevance is 82% lower, matching is 37% lower, and earnings volatility is 476% higher.

Because new firms have lower EQ measures than seasoned firms, the addition of new firms to the firm population should lower overall average EQ measures. I quantify this effect by disaggregating the changes in average EQ measures over the sample period of 1970 to 2009 into new-list and seasoned-firm effects. The seasoned-firm effect reflects the decline in

[2] Fama and French (2004) find seasoned firms to be relatively large firms with high survival rates and stable profits, but low growth prospects.

average EQ measures with no new firms joining the firm sample. The new-list effect is the change in average EQ measures that results from of the addition of new firms. I measure the new-list effect by the difference between the average EQ measures of the new- and seasoned-firm segments multiplied by the increases in the percentage of new firms in the firm population. I find that the new-list effect contributes as much as 73.9%, 80.0%, and 92.9% to the changes in average relevance, matching, and volatility, respectively, from the period 1970–1974 to the period 2005–2009. Hence, I show that the bulk of the changes in EQ measures over the last 40 years is due to the assimilation of newly listed firms into the firm population and not to changes in the EQ measures of existing firms. This is my main contribution to the literature.

In addition, I find that the biggest factor behind the new-list effect is the widening gap between the intangible intensities of the new- and seasoned-firm segments. Thus, changes in GAAP cannot be the main reason for the observed decline in earnings quality because the standards that require immediate expensing of in-house intangible investments have existed since the early 1970s.[3] Nevertheless, to control for changes in GAAP, I estimate trends in the properties of earnings by using the cash components of revenues, expenses, and earnings, which should be less affected by changes in GAAP (Dichev and Tang, 2008).[4] I find trends similar to those based on the accounting numbers. For example, successive firm cohorts display increasing volatility in operating cash flows, reflective of their increasing business risks (Fama and French, 2004). Hence, I conclude that the observed changes in average EQ measures have more to do with changes in average firm characteristics than with changes in GAAP. With this finding, I also contribute to the debate on whether the decline in earnings relevance over time is associated with increases in intangibles [Collins et al. (1997, p. 42) versus Francis and Schipper (1999, p. 321)]. I find a strong association between these two trends. However, I offer a more nuanced interpretation. I show that this phenomenon represents a shift in the firm population toward intangible-intensive firms due to new listings, rather than a general increase in the intangible intensity of all firms.

My findings differ from the literature in several respects. For example, I find that most of the observed declines in earnings relevance and matching reflect changes in the sample of firms. In contrast, Lev and Zarowin (1999, p. 358) and Dichev and Tang (2008, p. 1426), who also examine changing samples, conclude that the decline in average EQ measures is unrelated to the changes in their sample firms. Furthermore, my finding that the average matching and the volatility of core costs (McVay, 2006) have significantly changed over time differs from that of Donelson et al. (2011, p. 950). Additionally, I extend Givoly and Hayn (2000, p. 313) and Dichev and Tang (2008, p. 1452) by showing that the increase in the volatility of operating cash flows over time is a significant factor in the increase in earnings volatility. The differences between my study and the literature arise because I include firms listed in the 1990s and the first decade of the 2000s, whereas previous studies largely exclude those firms. These new firms make up three-quarters of the listed firm population today, use large amounts of intangible inputs, and display significantly lower EQ measures than do seasoned firms.

The rest of the paper proceeds as follows. Section 2 summarizes the literature and presents the hypotheses. Section 3 describes the sample selection, the measurement of the variables, and the correlational tests. Section 4 describes the tests of the hypotheses and examines the factors that cause the new-list effect. Section 5 presents concluding remarks.

2. Prior research, theory, and motivation of hypotheses

2.1. Prior research

Dechow et al. (2010) summarize the research on the changes in the properties of earnings over time. A brief summary of that research follows. Lev and Zarowin (1999) and Collins et al. (1997) document a decline in the relevance of earnings; Givoly and Hayn (2000) and Dichev and Tang (2008) find increases in the volatility of earnings; and Dichev and Tang (2008) find a decline in the matching of concurrent revenues and expenses. These studies interpret such trends as a decline in the quality of earnings.

However, the literature disagrees on whether it is changes in the real economy or changes in GAAP that have caused the declines in earnings quality. For example, Lev and Zarowin (1999, p. 358) conclude that "the declining returns-earnings association is not the result of new firms joining the sample." Similarly, Dichev and Tang (2008, p. 1426) find that the decline in matching is not driven by changes in the industry composition of the firm population, the characteristics of the sample firms, or the real economy. Also, Francis and Schipper (1999, p. 321) find no difference between the levels of, or changes in, the earnings relevance of high- and low-technology firms. In contrast, Collins et al. (1997, p. 59) find that the decline in earnings relevance is related to increases in the percentage of intangible-intensive industries. Additionally, Donelson et al. (2011) conclude that the decline in matching is related to the increases in special items that arise from both economic developments and changes in GAAP.

However, none of these studies includes firms listed in the late 1990s and the first decade of the 2000s, which now constitute a significant portion of the listed firm population (details described in Section 3). Thus, I reexamine changes in the

[3] SFAS No. 2 (FASB, 1974) requires an immediate expensing of R&D outlays. Some subsequent changes include a modification in the rule for reporting advertising expenses (Heitzman et al., 2010). In addition, SOP 98-1 (AICPA 1998) permits the selective capitalization of software-development costs, which should reduce reported R&D expenses. I find similar results by excluding advertising expenses and software firms.

[4] For example, the cash received from revenue transactions is less affected by changes in revenue recognition standards than are reported revenues (Altamuro et al., 2005).

properties of earnings by using more recent time-series data than do most prior studies. I respond to Dechow et al. (2010, p. 345), who call for more research on "how fundamental performance affects earnings quality." I also respond to Collins et al. (1997, p. 65), who call for an investigation into the effects of changes in industry composition and the resultant variation in the properties of earnings.

2.2. Changes in economic conditions over time

From the latter part of the twentieth century to the outset of the twenty-first century, the United States has moved from being an industrial economy to becoming a knowledge and services economy (Baumol and Schramm, 2010). Consequently, the demand for informational products has replaced the demand for many physical products (Shapiro and Varian, 1998). The literature offers probable reasons for the increases in the service and knowledge sectors of the U.S. economy. On a conceptual level, Keynes (1930) forecasted that technological improvements and rising productivities would lead to everyone experiencing more fun, leisure, and pleasure. Since Keynes's prediction, technological and agricultural productivities have improved significantly (Clark, 2010). As a result, the relative prices of basic goods have declined by two-thirds during the twentieth century (Zanias, 2005). In addition, Aguiar and Hurst (2007) find significant increases in leisure hours since 1965. Because of these developments, the demand for knowledge products and services has increased at a faster rate than the demand for physical products (Apte et al., 2008).

Further, while the United States built comparative advantages in the industrial sector through much of the twentieth century, these advantages had largely eroded by the dawn of the twenty-first century (Sachs and Schatz, 1994). In contrast, over the last few decades, the United States has built comparative advantages through innovation, ideas, knowledge, and competencies (Crescenzi et al., 2007; Bartram et al., 2012). The use of knowledge has also expanded because of increases in economies of scale and scope that have resulted from greater globalization (Romer, 1986; Jones and Romer, 2010). Technological developments have aided the growth of knowledge businesses by reducing consumers' search costs (Bakos, 1997), by facilitating instantaneous and low-cost delivery of knowledge products to remote customers (Spohrer and Engelbart, 2004), and by enabling a quicker assimilation of existing knowledge products into the creation of new knowledge products (Shapiro and Varian, 1998).

Apte et al. (2008) quantify the temporal increases in U.S. firms' intangible inputs by dividing the U.S. economy into two distinct domains. The first is the material domain, which transforms "matter and energy from one form into another." The second is the knowledge domain, which transforms "information from one pattern into another." Apte et al. (2008) show that the share of U.S. gross domestic product (GDP) deriving from the material domain declined from 71% in 1958 to 37% in 1997. Over this period, the economic share of the knowledge domain increased to 63% of U.S. GDP.

Furthermore, using macro-level indicators, Corrado and Hulten (2010) estimate aggregate expenditures in innovation, marketing, customer support, human capital, computerized data and algorithms, and organizational development by U.S. firms. They refer to these expenditures as "investments." They argue that savings occur when resources are used to provide future, not current, benefits. They estimate that U.S. firms' annual intangible investments more than doubled from 5.9% of U. S. GDP in the early 1970s to 11.3% by the end of the first decade of the 2000s.

2.3. Motivation for H1: successive cohorts' increasing knowledge intensity

Because knowledge-intensive firms mainly transform information from one pattern to another (Apte et al., 2008), the creation of knowledge products should require a higher proportion of intangible inputs, such as R&D, expert human capital, databases, and information technology, relative to the manufacture of physical goods. Analogously, knowledge production should consume fewer material inputs. Further, an increasing percentage of new firms coevolving with economic trends are likely to pursue knowledge-based businesses. Thus, successive cohorts of listed firms should use an increasing percentage of intangible inputs in their production functions.

To the extent that seasoned firms continue to pursue mature industrial businesses, they are unlikely to radically change their production functions (Hambrick, 1983; Fama and French, 2004; Chen et al., 2010).[5] Specifically, these firms are unlikely to significantly reduce their materials and energy usage unless breakthroughs in production technologies occur.[6] However, seasoned firms might exploit IT developments to increase their intangible intensity (Porter, 1985). Whether seasoned firms increase their intangible intensity and whether these increases are sufficient to keep pace with the increasing intangible intensity of the successive cohorts of new firms remain empirical questions.

[5] In the mature phases of an industry's lifecycle, the marketplace becomes relatively stable and firms avoid sudden, large moves to keep the beneficial status quo (Chen et al., 2010).

[6] Outsourcing of production activities merely replaces one form of product costs [in-house cost of goods sold (COGS)] with another (purchased COGS). For example, Ford has progressively increased outsourcing and has increased its focus on product design, brands, and customer relationships (Lev, 2001). Yet its COGS to total expense ratio has changed little—from 84.6% in 1970 to 82.9% in 2009. Contrast these COGS ratios against those of knowledge firms: Pfizer and Microsoft have average COGS ratios of just 31.9% and 19.1%, respectively.

I use SG&A intensity as a proxy for intangible intensity because firms typically expense in-house intangible expenditures through SG&A accounts (Banker et al., 2011; Eisfeldt and Papanikolaou, 2013).[7] I also use R&D expenditures and market-to-book ratios as additional proxies for intangible intensity (Francis and Schipper, 1999). Thus, I hypothesize the following:

H1A. Successive cohorts of new firms exhibit increasing SG&A intensities.

Intangible expenditures can generate benefits in the future (Lev and Sougiannis, 1996; Ittner and Larcker, 1998; Brynjolfsson and Hitt, 2000). Yet these outlays are typically expensed as incurred and are reported as SG&A expenses (Banker et al., 2011). This immediate expensing of intangible outlays should lower the correlation between SG&A expenses and current revenues. Further, increases in immediately expensed intangible outlays, to the extent that they are sporadically incurred, should increase year-to-year volatility in SG&A expenses. This effect is similar to increases in expense volatilities if property, plant, and equipment (PP&E) outlays were immediately expensed. This discussion leads to two hypotheses:

H1B. Successive cohorts of new firms exhibit decreasing matching between concurrent SG&A expenses and revenues.

H1C. Successive cohorts of new firms exhibit increasing volatility in SG&A expenses.

2.4. Motivation for H2: successive cohorts' decreasing EQ measures

At least two economic developments in the U.S. business environment should reduce average EQ measures. The first is the increase in business competitiveness and uncertainty (Irvine and Pontiff, 2005). This development increases firms' idiosyncratic stock-return volatilities and lowers firms' survival rates (Campbell et al., 2001; Fama and French, 2004). This development should also increase special items because of more frequent asset impairments, restructuring, and gains or losses from asset sales (Donelson et al., 2011). Increases in special items should reduce EQ measures for the following reasons. Special items are less correlated with current revenues than are other expenses, thus reduce matching (Donelson et al., 2011). Moreover, special items are less persistent than other earnings components, thus they increase the volatility of earnings (Fairfield et al., 1996; Givoly and Hayn, 2000; Jones and Smith, 2011). The resulting increase in volatility should lower the relevance of earnings (Elliott and Hanna, 1996).

The other significant development in the U.S. economy is the increase in firms' intangible usage. This development is likely to change EQ measures by affecting firms' business performance and their financial reports. As discussed in Section 2.3, the immediate expensing of intangible outlays intended to produce future revenues should reduce matching. In addition, any year-to-year fluctuations in intangible investments should increase the volatility of earnings because current revenues might not increase or decrease with investments. Further, intangible-intensive firms should exhibit high earnings volatility because their investments carry high uncertainty about future benefits (Kothari et al., 2002). The resultant increases in earnings volatility should reduce investors' ability to project a firm's future performance (Barton et al., 2010), thereby reducing the relevance of earnings. Furthermore, relative to material-intensive firms that typically have assets-in-place, which are recognized in financial reports, intangible-intensive firms are likely to have a higher proportion of growth options, which are not recognized in financial statements unless they are purchased (Smith and Watts, 1992; Watts, 2003; Skinner, 2008). Specifically, the values and the changes in values of growth options are typically not recognized in the balance sheet and the income statement (Roychowdhury and Watts, 2007). Therefore, intangible-intensive firms are likely to exhibit lower earnings relevance than material-intensive firms.

Because I expect successive cohorts of new firms to show increasing intangible intensity, I hypothesize the following:

H2A. Successive cohorts of new firms exhibit decreasing matching between concurrent revenues and expenses.

H2B. Successive cohorts of new firms exhibit increasing volatility in earnings.

H2C. Successive cohorts of new firms exhibit decreasing relevance of earnings.

3. Sample selection, measurement of key variables, and correlational tests

I use 189,608 firm-year observations with valid data from the years 1970 through 2009. I exclude all finance firms because the traditional cost classifications, i.e., cost of goods sold (COGS) versus SG&A, do not apply to these firms. In addition, I exclude the industry categorized as “almost nothing” in the Fama–French classification (Fama and French, 1997), as it is difficult to interpret its results in an industry context. Thus, I exclude the Fama–French industries identified by numbers 44–47 (representing finance firms) and 48 (representing “almost nothing”), which leaves 43 industries. The first year in which a firm's data are available in Compustat is referred to as the “listing year.”[8] All of the firms with a listing year before 1970 are classified as “seasoned firms” (Fama and French, 2004). The remaining firms are classified as “new firms.” All of the cohorts listed in a common decade are referred to as a “wave” of new firms (Brown and Kapadia, 2007).

[7] The measurement of SG&A intensity is described in Section 3.2.1.

[8] Alternatively, I could use the first year of data availability in the Center for Research in Security Prices (CRSP) as the listing year. I find qualitatively similar results using CRSP-based listing years. I opt to use the listing year based on Compustat data availability to align my sample with the empirical tests.

Table 1
The number of firm-year observations from the successive listing cohorts in each year.

This table presents the number of firm-year observations from the successive listing cohorts in each year from 1970 to 2009. All of the firms are divided into five listing cohorts in the following steps. The first year in which a firm's data are available in Compustat is referred to as the "listing year." All of the firms with a listing year before 1970 are classified as "seasoned firms." The remaining firms are classified as "new firms." All of the cohorts listed in a common decade are referred to as a "wave" of new firms. Consequently, all of the firms are divided into seasoned firms or a wave from the 1970s, 1980s, 1990s, or 2000s.

Fiscal year	Total number of firms	Seasoned firms	New firms			
			1970s wave	1980s wave	1990s wave	2000s wave
1970	2,470	**2,304**	166			
1971	2,786	2,263	523			
1972	2,975	2,219	756			
1973	3,121	2,169	952			
1974	3,206	2,108	1,098			
1975	3,213	2,051	1,162			
1976	3,214	1,977	1,237			
1977	3,105	1,886	1,219			
1978	3,051	1,806	1,245			
1979	3,247	1,731	**1,516**			
1980	3,510	1,657	1,413	440		
1981	3,656	1,587	1,336	733		
1982	4,109	1,533	1,264	1,312		
1983	4,273	1,428	1,160	1,685		
1984	4,396	1,348	1,046	2,002		
1985	4,526	1,257	978	2,291		
1986	4,544	1,186	900	2,458		
1987	4,661	1,098	822	2,741		
1988	4,629	1,024	760	2,845		
1989	4,636	970	705	**2,961**		
1990	4,684	944	667	2,712	361	
1991	4,868	935	650	2,538	745	
1992	5,098	921	636	2,371	1,170	
1993	5,319	905	602	2,159	1,653	
1994	5,713	873	578	1,986	2,276	
1995	6,166	847	555	1,877	2,887	
1996	6,593	813	539	1,913	3,328	
1997	6,578	757	502	1,783	3,536	
1998	6,635	705	461	1,629	3,840	
1999	6,500	651	417	1,506	**3,926**	
2000	6,347	605	393	1,384	3,495	470
2001	6,399	586	366	1,286	3,185	976
2002	6,183	561	351	1,190	2,839	1,242
2003	6,076	546	328	1,121	2,622	1,459
2004	5,852	524	311	1,037	2,407	1,573
2005	5,755	510	296	956	2,201	1,792
2006	5,597	472	276	882	1,989	1,978
2007	5,482	455	267	822	1,813	2,125
2008	5,344	443	257	791	1,677	2,176
2009	5,091	431	242	735	1,555	**2,128**
Percentage of firms that survived in 2009 from the last year of formation of that listing cohort (highlighted in bold letters)						
		18.71	15.96	27.10	44.49	100.00
Breakdown by listing cohorts in 2009						
Numerical proportion (%)		8.47	4.75	14.44	30.54	41.80
Market capitalization (%)		25.92	7.91	17.72	24.40	24.06

Consequently, all of the firms are divided into seasoned firms or a wave from the 1970s, 1980s, 1990s, or 2000s. Table 1 shows the annual distribution of firm-year observations by waves.

3.1. Changes in the composition of the Compustat firm population

The firm population refers to firms with valid data in Compustat.[9] Table 1 describes how the firm population changed during the 40-year study period. In 1970, there were 2,470 firms. From 1970 to 1997, the firm population increased to 6,578, at a compounded annual growth rate of 3.6%. The firm population declined thereafter to 5,091 in 2009.

[9] For reasons discussed in Section 3.2, each firm-year observation requires data on assets; earnings; revenues from the previous two years, the current year, and the next year; and stock-price data from the end of the previous and current years.

Before 1970, the firm population consisted entirely of seasoned firms, by definition. At the end of 2009, the percentage of seasoned firms stood at just 8.5%, respectively. Thus, from 1970 to 2009, the dominant firm-population segment changed from the seasoned-firm segment to the new-firm segment. Therefore, the changes in the average EQ measures over time should be related to changes in the sample of firms if EQ measures differ for seasoned and new firms.

3.2. Measurement of variables

3.2.1. SG&A intensity

Following Dichev and Tang (2008), I first calculate "total expenses" by subtracting income before extraordinary items (Compustat IB) from revenues (Compustat SALES). I measure COGS and SG&A expenses by the Compustat data items COGS and XSGA, respectively. Consistent with McVay (2006), I refer to the sum of COGS and SG&A as "core expenses." I call the other expenses "noncore." I calculate the relative proportions of the three types of expenses (COGS, SG&A, and noncore expenses) for each firm-year by dividing them by that firm-year's total expenses and refer to them as "SG&A intensity," "COGS intensity," and "noncore intensity," respectively.

3.2.2. Volatility of SG&A expenses, total expenses, revenues, and earnings

Following Givoly and Hayn (2000, p. 313) and Dichev and Tang (2008, p. 1441), I scale SG&A expenses, revenues, total expenses, and earnings by the average of the beginning and ending total assets. I then estimate the standard deviations of these variables for each firm-year using four rolling annual observations ($t-2$ through $t+1$).[10]

3.2.3. Matching

Following Dichev and Tang (2008, Table 3, p. 1436), I estimate the following regression on an annual cross-sectional basis for each wave-year:

$$Revenues_{i,t} = \beta_{1,t} + \beta_{2,t} \times TotalExpenses_{i,t-1} + \beta_{3,t} \times TotalExpenses_{i,t} + \beta_{4,t} \times TotalExpenses_{i,t+1} + \varepsilon_{i,t} \quad (1)$$

I scale all of the variables by average total assets. I measure "matching" by the regression coefficient on the contemporaneous expenses (β_3), which represents the contemporaneous revenue–expense correlation. I measure the "forward association" by the coefficient on past expenses (β_2) that represents the correlation between expenses and future revenues.

Similarly, I measure the matching of SG&A expenses by β_4 in the following equation:

$$Revenue_{i,t} = \beta_1 + \beta_2 \times TotalExpense_{i,t-1} + \beta_3 \times COGS_{i,t} + \beta_4 \times SG\&A_{i,t} + \beta_5 \times NoncoreExpenses_{i,t} + \beta_6 \times TotalExpenses_{i,t+1} + \varepsilon_{i,t} \quad (2)$$

3.2.4. Relevance

Consistent with Easton and Harris (1991, Table 3, p. 31), I estimate the following regression on an annual cross-sectional basis for each wave-year:

$$Ret_{i,t} = \beta_{1,t} + \beta_{2,t} \times \Delta Earnings_{i,t} + \beta_{3,t} \times Earnings_{i,t} + \varepsilon_{i,t} \quad (3)$$

These variables are defined in Appendix A. I measure the "relevance" of earnings by the adjusted R-square of the above regression.

3.3. Industry analysis

Before testing the hypotheses, I examine the principal ideas that underlie H1 and H2. Specifically, I examine whether successive firm cohorts pursue more knowledge-intensive businesses and whether EQ measures decline with intangible intensity. These tests also respond to Collins et al. (1997, p. 65), who call for an investigation into the effects over time of changes in the industry composition of the listed firm population.

3.3.1. Changes in industry composition

I assign "wave-order" values of 1 to seasoned firms and 2, 3, 4, and 5 to firms from the 1970s, 1980s, 1990, and 2000s waves, respectively. For example, firms listed in 1955 and 2006 are assigned wave-order values of 1 and 5, respectively. I categorize all of the firms by the Fama–French 48-industry classification. I calculate an industry's "recency" by averaging the wave-order values of all of its pooled firm-year observations from 1970 to 2009. Therefore, an industry with observations only from the seasoned-firm category has a recency of 1. Similarly, an industry with observations only from firms from 2000s wave has a recency of 5. Thus, an industry's recency ranges from 1 to 5—the higher the recency, the higher is the proportion of firm-year observations coming from the most recent waves.

[10] Using this method ($t-2$ through $t+1$) instead of using observations ($t-3$ through t) makes the data requirements consistent with those of Eq. (1). Nevertheless, I lose the first observation of each wave because I do not have asset data for year $t-3$ to estimate the average total assets for the year $t-2$.

I sort the industries by the highest to lowest values of recency and present them in Panel A of Table 2. This table shows that the ten industries with the highest recency are pharmaceuticals (recency of 3.48), business services (3.34), gold and precious metals (3.30), healthcare (3.24), medical equipment (3.14), communication (3.10), computers (3.09), entertainment (3.01), electronic equipment (2.85), and personal services (2.85). All of these industries are innovation and knowledge intensive except for the gold and precious metals industry. The ten industries with the lowest recency are utilities (1.49), aircraft (1.73), tobacco products (1.85), shipbuilding and railroad equipment (1.87), textiles (1.92), shipping containers (1.93), business supplies (1.94), construction materials (1.97), food products (2.05), and steel (2.10).

Panel A of Table 2 also shows the average attributes of each industry based on all of its pooled firm-year observations from 1970 to 2009. For expositional purposes, I highlight the five industries with the highest (lowest) values in each attribute by using bold (bold italic) letters. This panel shows that in general, industries with the highest recency have the highest market-to-book ratios and SG&A intensity. Furthermore, in unreported tests, I find that each new wave of firms exhibits higher growth and higher stock-return volatility than its predecessors (Brown and Kapadia, 2007). In contrast, I find seasoned firms to be relatively large firms with low growth (Fama and French, 2004). Taken together, the results show that new firms increasingly pursue evolving, knowledge-intensive businesses but seasoned firms largely continue to operate in mature, material-intensive industries.

3.3.2. Correlational tests

Panel B of Table 2 presents the Pearson and Spearman's rank correlations among the average attributes of the industries. These correlations support the principal ideas underlying this study. First, SG&A intensity is negatively correlated with matching (correlation coefficient of −0.640 and significant at a p-value < 0.01) but positively correlated with forward association (results not reported). These correlations are consistent with the idea that intangible investments are often immediately expensed and reported in the SG&A category of expenses. Second, SG&A intensity is strongly correlated with the market-to-book ratio (correlation coefficient of 0.787 and significant at a p-value < 0.01). This correlation indicates that a measure based on SG&A expenses is consistent with a widely used measure of intangible intensity. Third, SG&A intensity is negatively correlated with relevance (correlation coefficient of −0.360 and significant at a p-value of 0.02) and positively correlated with earnings volatility (correlation coefficient of 0.732 and significant at a p-value < 0.01). These correlations indicate that the immediate expensing of investment outlays reduces the three EQ measures. Also, the correlations among the EQ measures indicate that relevance improves with matching (correlation coefficient of 0.463 and significant at a p-value < 0.01) but declines with earnings volatility (correlation coefficient of −0.512 and significant at a p-value < 0.01).

Other correlations provide preliminary support for my hypotheses. Recency is positively correlated with both SG&A intensity and the market-to-book ratio (correlation coefficients of 0.652 and 0.756, respectively, and both significant at a p-value < 0.01). Consistent with H1A, which posits that successive firm cohorts exhibit increasing SG&A intensities, these correlations indicate that industries with more recently listed firms exhibit higher intangible intensity. Also, recency is negatively and positively correlated with SG&A matching and volatility, respectively (correlation coefficients of −0.408 and 0.774 and both significant at a p-value < 0.01). These correlations show that industries with more recently listed firms have lower SG&A matching but higher SG&A volatility, consistent with hypotheses H1B and H1C, respectively. In addition, recency is negatively correlated with matching and relevance (correlation coefficients of −0.710 and −0.459, respectively, and both significant at a p-value < 0.01) and positively correlated with earnings volatility (correlation coefficient of 0.834 and significant at a p-value < 0.01). These correlations indicate that industries with recently listed firms exhibit low EQ measures, which is consistent with H2A, H2B, and H2C.

4. Tests of hypotheses

4.1. H1A: successive waves' increasing SG&A intensity

I first calculate the cross-sectional average of SG&A intensity by wave-year. This calculation results in 140 wave-year averages made up of 40 annual observations for the seasoned-firm category (1970–2009) and 40 (1970–2009), 30 (1980–2009), 20 (1990–2009), and ten (2000–2009) annual observations for the 1970s, 1980s, 1990s, 2000s waves, respectively. I then calculate the overall average of the annual wave-year averages for each wave. The first column of Panel A in Table 3 shows that average SG&A intensities for seasoned firms and for the 1970s, 1980s, 1990s, and 2000s waves are 16.2%, 21.8%, 29.5%, 29.5%, and 38.3%, respectively. This pattern indicates increasing intangible intensity across successive cohorts of listed firms. Because COGS and SG&A constitute approximately 89% of the firms' total costs, I find opposite patterns for COGS intensity. Specifically, the second column of Panel A in Table 3 shows decreasing COGS intensities of 72.9%, 67.3%, 58.9%, 58.6%, and 47.9%, respectively, indicating decreasing material intensity.[11]

Nevertheless, the above averages might not be comparable across waves because they are calculated over different periods. Thus, the above patterns could simply represent overall time trends. For example, the average for the 2000s wave is calculated using only ten wave-year observations. In contrast, the average for the seasoned firms is calculated using 40

[11] COGS represent the costs of procurements of goods or the costs of direct and indirect labor, material, and energy required for the production of goods.

Table 2
Cross-sectional analysis: intangible intensity; recency; selling, general, and administrative expenses (SG&A) attributes; and earnings quality by Fama–French 48-industry classification.

All of the firms are classified by the Fama–French 48-industry method. Four industries representing the finance firms and one "almost nothing" category are excluded. Panel A presents the average attributes of each industry calculated by using all of the pooled observations from that industry from 1970 to 2009. These attributes are calculated by using the methods described in Appendix A. The top (bottom) five industries for each attribute are highlighted in bold (bold italic) letters. All of the industries are sorted by the highest to lowest values of recency, which is calculated in the following steps. First, the firms listed before 1970 and the firms listed in the 1970s, 1980s, 1990s, and the first decade of 2000s are assigned the "wave-order" values of 1, 2, 3, 4, and 5, respectively. Then, an industry's "recency" is calculated by averaging the wave-order values of all of its pooled firm-year observations. The higher the recency, the higher is the percentage of firm-year observations from the most recently listed firms.

Panel A: The average attributes of industries

Fama–French industry code		Composition	Intangibles	SG&A attributes			Earning quality measures		
	Industry name	Recency	Market-to-book Ratio	Intensity (%)	Matching	Volatility	Earnings volatility	Matching	Relevance (%)
13	Pharmaceutical Products	**3.48**	**4.25**	35.88	0.32	**0.13**	**0.26**	***0.33***	***1.39***
34	Business services	**3.34**	**2.81**	35.54	0.48	0.09	**0.19**	0.80	2.59
27	Gold and precious metals	**3.30**	**2.80**	**37.56**	***−0.11***	**0.39**	**0.23**	***0.11***	***0.64***
11	Healthcare	**3.24**	1.97	20.86	0.66	0.06	0.11	0.82	3.61
12	Medical equipment	**3.15**	**3.24**	**45.23**	0.31	**0.12**	**0.18**	0.64	1.87
32	Communication	3.10	2.09	22.24	0.34	0.09	0.13	***0.60***	2.65
35	Computers	3.09	2.59	**37.35**	0.41	0.08	0.18	0.78	4.00
7	Entertainment	3.01	2.03	21.16	***0.11***	0.12	0.14	0.84	2.43
36	Electronic equipment	2.85	2.15	30.42	0.38	0.05	0.12	0.88	3.31
33	Personal services	2.85	1.88	26.10	0.90	0.04	0.06	0.90	5.12
30	Petroleum and natural gas	2.83	1.93	20.98	***−0.02***	**0.12**	0.13	0.72	2.93
29	Coal	2.83	1.47	12.35	0.39	0.05	0.07	0.95	4.56
3	Candy and soda	2.72	2.05	28.53	0.92	0.03	0.11	0.93	4.20
37	Measuring and control eqp	2.70	2.24	**37.78**	0.48	0.05	0.12	0.85	3.94
43	Restaurants, hotels	2.65	1.61	13.50	0.79	0.04	0.06	0.87	3.58
40	Transportation	2.58	1.43	***9.43***	0.69	0.03	0.05	0.94	2.72
28	Mining	2.55	**2.75**	**39.14**	***−0.09***	**0.33**	**0.21**	***0.26***	***0.79***
1	Agriculture	2.54	1.70	20.50	0.89	0.05	0.08	0.94	**10.14**
6	Recreation	2.50	1.85	28.80	0.17	0.05	0.14	0.95	1.90
41	Wholesale	2.49	1.60	19.87	0.67	0.04	0.08	0.98	2.74
42	Retail	2.46	1.56	25.31	0.94	0.02	0.05	0.97	6.05
18	Construction	2.42	1.34	12.78	0.79	0.04	0.06	**1.02**	3.68
22	Electrical equipment	2.37	2.03	26.29	0.23	0.05	0.10	0.88	3.15
26	Defense	2.36	1.92	16.05	**1.03**	0.04	0.07	**1.12**	9.51
4	Beer and liquor	2.34	1.86	27.64	0.86	0.03	***0.04***	***0.57***	5.93
15	Rubber and plastic	2.33	1.50	20.55	0.78	0.03	0.06	0.95	5.38
14	Chemicals	2.32	2.11	23.18	0.21	0.04	0.09	0.84	2.33
21	Machinery	2.30	1.87	25.27	0.15	0.04	0.10	0.95	***1.54***
20	Fabricated products	2.27	***1.17***	16.58	0.94	0.05	0.05	1.02	**17.36**
8	Printing and publishing	2.20	1.73	31.85	0.77	0.04	0.05	0.82	6.25
23	Automobiles and trucks	2.20	1.64	13.94	0.21	0.03	0.07	0.94	***0.63***
10	Apparel	2.19	1.35	24.09	0.94	0.02	0.05	0.99	**12.13**
9	Consumer goods	2.13	1.67	30.61	**0.97**	0.04	0.06	1.00	7.04
19	Steel works	2.10	***1.30***	***10.68***	0.39	0.03	0.06	1.00	4.44
2	Food products	2.05	1.59	19.72	0.94	0.03	0.05	0.97	2.11
17	Construction materials	1.97	1.34	17.54	0.82	0.03	0.05	1.02	8.31
38	Business supplies	1.94	1.36	17.49	**0.99**	***0.02***	***0.04***	0.97	8.09
39	Shipping containers	1.93	1.39	***11.77***	***0.08***	***0.02***	0.06	0.98	2.82
16	Textiles	***1.92***	***1.03***	13.43	**1.01**	***0.01***	***0.04***	**1.04**	**17.78**
25	Shipbuilding railroad eqp	***1.87***	***1.26***	***10.28***	**1.04**	***0.01***	***0.05***	**1.11**	**15.49**

5	Tobacco products	***1.85***	2.22	23.35	0.69	0.04	0.06	0.83	3.45
24	Aircraft	***1.73***	1.55	15.62	0.23	0.03	0.08	**1.08**	2.48
31	Utilities	***1.49***	***1.12***	***1.01***	0.50	***0.00***	***0.01***	1.00	7.65

Correlational tests

Panel B shows the correlations among the average attributes of the 43 industries presented in Panel A.

Panel B: Correlations among industry attributes

	$N=43$	Pearson correlation							
		Composition	Intangibles	SG&A attributes			EQ measures		
Spearman rank correlation		Recency	Market-to-book ratio	Intensity	Matching	Volatility	Earnings volatility	Matching	Relevance
	Recency	–	0.756	0.652	−0.408	0.774	0.834	−0.710	−0.459
	Market-to-book ratio	0.724	–	0.787	−0.458	0.897	0.893	−0.767	−0.526
	SG&A intensity	0.577	0.811	–	−0.279	0.847	0.732	−0.640	−0.360**
	SG&A matching	−0.396	−0.484	−0.262*	–	−0.406	−0.634	0.534	0.681
	SG&A volatility	0.716	0.871	0.848	−0.452	–	0.884	−0.597	−0.503
	Earnings volatility	0.777	0.795	0.587	−0.704	0.824	–	−0.771	−0.512
	Matching	−0.725	−0.826	−0.680	0.516	−0.643	−0.604	–	0.463
	Relevance	−0.444	−0.585	−0.329**	0.802	−0.604	−0.676	0.528	–

All correlations are significant at 1% level.

* Indicates significance at the 10% level.

** Indicates significance at the 5% level.

Table 3
The cost composition and intangible intensity of the successive listing cohorts.

Panel A presents the average attributes of the successive listing cohorts. All of the firms are divided into five listing cohorts in the following steps. The first year in which a firm's data are available in Compustat is referred to as the "listing year." All of the firms with a listing year before 1970 are classified as "seasoned firms." The remaining firms are classified as "new firms." All of the cohorts listed in a common decade are referred to as a "wave" of new firms. Consequently, all of the firms are divided into seasoned firms or a wave from the 1970s, 1980s, 1990s, or 2000s. All attributes are first calculated on a wave-year basis by using the methods described in Appendix A. These methods result in 40 annual observations for the seasoned-firm category (1970–2009), 40 annual observations for the 1970s wave (1970–2009), 30 annual observations for the 1980s wave (1980–2009), 20 annual observations for the 1990s wave (1990–2009), and 10 annual observations for the 2000s wave (2000–2009) for each attribute. Volatility has one fewer observation per wave. The overall average attribute of a listing cohort is calculated by averaging all of its annual attributes.

Panel A: The average characteristics of the successive listing cohorts

	Composition of total costs			Other measures of intangible intensity		Attributes of SG&A expenses	
Listing cohort	SG&A intensity (%)	COGS intensity (%)	Noncore intensity (%)	R&D intensity (%)	Market-to-book ratio	SG&A matching	SG&A volatility
Seasoned firms	16.2	72.9	10.9	1.13	1.39	1.05	0.024
1970s wave	21.8	67.3	11.0	1.94	1.61	0.9	0.051
1980s wave	29.5	58.9	11.6	5.47	2.56	0.54	0.100
1990s wave	29.5	58.6	11.9	8.15	2.52	0.55	0.097
2000s wave	38.3	47.9	13.8	9.39	3.53	0.1	0.25

Differences in the SG&A attributes of the successive listing cohorts after controlling for overall time trends

Panel B examines whether the attributes of SG&A expenses (intensity, matching, and volatility) differ across successive listing cohorts after controlling for overall time trends. All of the firms are divided into five listing cohorts in the following steps. The first year in which a firm's data are available in Compustat is referred to as the "listing year." All of the firms with a listing year before 1970 are classified as "seasoned firms." The remaining firms are classified as "new firms." All of the cohorts listed in a common decade are referred to as a "wave" of new firms. Consequently, all of the firms are divided into seasoned firms or a wave from the 1970s, 1980s, 1990s, or 2000s. All of the SG&A attributes are calculated on a wave-year basis by using the methods described in Appendix A. Then the following regression is estimated by using 140 wave-year observations, comprising 40 annual observations for the seasoned-firm category (1970–2009), 40 annual observations for the 1970s wave (1970–2009), 30 annual observations for the 1980s wave (1980–2009), 20 annual observations for the 1990s wave (1990–2009), and ten annual observations for the 2000s wave (2000–2009). Volatility has one less observation per wave.

$$SG\&AAttribute_{Wave,year} = \beta_1 + \beta_2 \times FiscalYear + \gamma_1 \times DummyListYear1970\_79 + \gamma_2 \times DummyListYear1980\_89 + \gamma_3 \times DummyListYear1990\_99 + \gamma_4 \times DummyListYear2000\_09 + \varepsilon_{Wave,year},$$

where the dummy variables *DummyListYear1970_79*, *DummyListYear1980_89*, *DummyListYear1990_99*, and *DummyListYear2000_09* take the value of one for the wave-year observations of the 1970s, 1980s, 1990s, and 2000s waves, respectively, and zero otherwise. Because a dummy variable for the seasoned-firm observations is not included in the above regression, they form the base case.

Panel B: Differences in the SG&A attributes of the successive listing cohorts

	SG&A intensity		SG&A matching		SG&A volatility	
	Estimate	*t*-Statistic	Estimate	*t*-Statistic	Estimate	*t*-Statistic
Intercept	−1.322	−5.02***	23.318	8.15***	−1.619	−4.26***
Fiscal Year × *1,000*	0.746	5.63***	−11.192	−7.78***	0.825	4.32***
DummyListYear1970_79	0.057	16.11***	−0.151	−4.00***	0.026	5.48***
DummyListYear1980_89	0.129	34.11***	−0.451	−10.93***	0.071	13.34***
DummyListYear1990_99	0.126	28.24***	−0.389	−7.99***	0.065	10.17***
DummyListYear2000_09	0.211	36.09***	−0.776	−12.29***	0.213	24.45***
N		140		140		135
F-value		522***		88***		182***
Adjusted *R*-square (%)		94.94		75.76		87.36
F-tests		*p*-Value		*p*-Value		*p*-Value
Average Seasoned firms = 1970s wave (γ_1)		< 0.001		0.001		< 0.001
Average 1970s wave = 1980s wave ($\gamma_1 = \gamma_2$)		< 0.001		< 0.001		< 0.001
Average 1980s wave = 1990s wave ($\gamma_2 = \gamma_3$)		0.417		0.189		0.315
Average 1990s wave = 2000s wave ($\gamma_3 = \gamma_4$)		< 0.001		< 0.001		< 0.001

*** Indicates statistical significance (two-sided) at the 1% level.

wave-year observations. Thus, the seasoned-firms' average includes the earliest observations from the sample period, which are characterized by the lowest intangible usage. To control for overall time trends, I estimate the following regression, which is similar to Brown and Kapadia (2007, p. 374):

$$SG\&A - Intensity_{Wave,Year} = \beta_1 + \beta_2 \times Year + \gamma_2 \times DummyListYear1970\_79$$

$$+\gamma_3 \times DummyListYear1980\_89 + \gamma_4 \times DummyListYear1990\_99$$
$$+\gamma_5 \times DummyListYear2000\_09 + \varepsilon_{Wave,Year} \quad (4)$$

I use 140 wave-year observations to estimate this regression. The *Year* variable controls for the overall time trend. The dummy variables *DummyListYear1970_79*, *DummyListYear1980_89*, *DummyListYear1990_99*, and *DummyListYear2000_09* take the value of one for the wave-year observations of the 1970s, 1980s, 1990s, and 2000s waves, respectively, and zero otherwise. Because I do not include a dummy variable for the observations of seasoned firms, they form the base case. Hence, the coefficients on the dummy variables represent the differences between the waves' and the seasoned firms' averages after controlling for overall time trends.

The first column of Panel B in Table 3 shows that the coefficients on all of the wave dummies are positive and significant. Thus, each new cohort shows higher SG&A intensity relative to the seasoned firms. In addition, the *F*-tests on the differences in the regression coefficients of the other successive waves (that is, γ_1 versus γ_2, γ_2 versus γ_3, and γ_3 versus γ_4) suggest that each successive wave exhibits higher SG&A intensity than its predecessor. The only exception is that I do not find a significant difference between the 1980s and 1990s waves.[12]

I use Eq. (4) to test the subsequent hypotheses by using alternative dependent variables. Therefore, for brevity, I do not repeat this equation or the manner of its interpretation.

4.1.1. Additional tests using R&D and market-to-book ratios

I calculate the average R&D intensity and market-to-book ratio for each wave (formulae described in Appendix A). The fourth column of Panel A in Table 3 shows that the successive waves exhibit increasing R&D intensity of 1.13%, 1.94%, 5.47%, 8.15%, and 9.39%. Similarly, the fifth column shows that the successive waves exhibit increasing market-to-book ratios of 1.39, 1.61, 2.56, 2.52, and 3.53. These findings, along with the SG&A intensity results, provide consistent evidence that the successive waves display increasing intangible intensity.

4.2. H1B and H1C: successive waves' decreasing SG&A matching and increasing SG&A volatilities

The sixth column of Panel A in Table 3 shows that the successive waves exhibit declining SG&A matching of 1.05, 0.90, 0.54, 0.55, and 0.10. I estimate Eq. (4) to control for overall time trends and find similar results, as shown in the second column of Panel B in Table 3. Further, in unreported tests, I find a declining trend in average SG&A matching for the firm population.[13] In this respect, my results differ from those of Donelson et al. (2011), who find no temporal decline in average SG&A matching. This difference arises because Donelson et al. (2011) largely exclude new firms from their study sample.[14]

The seventh column of Panel A in Table 3 shows that successive waves have increasing SG&A volatility of 0.02, 0.05, 0.10, 0.10, and 0.25. The third column of Panel B in Table 3 shows similar trends despite controlling for overall time trends. Arguably, this increase in SG&A volatility reflects increases in one-off core costs that are expensed as incurred, such as senior executive hiring, brand launches, IT system installations, advertising campaigns, and market-research projects. As a result, the total-expense volatility shows an increasing pattern of 0.13, 0.20, 0.27, 0.27, and 0.47 (the third column of Panel A in Table 4). In this respect, my findings differ from those of Dichev and Tang (2008), who find no temporal increase in average expense volatility. However, as noted in footnote 14, Dichev and Tang (2008) also largely exclude new firms from their study.

4.3. H2A: successive waves' decreasing matching

If COGS matching is held constant, then a reduction in SG&A matching and an increase in SG&A intensity should lower the matching of total expenses. Indeed, the matching of total expenses across successive waves shows a decreasing pattern of 1.00, 0.96, 0.80, 0.77, and 0.38 (the first column of Panel A in Table 4). The first column of Panel B in Table 4 shows similar results despite controlling for overall time trends. Further, I find similar results after controlling for special items (results not reported). The forward association shows an increasing pattern (results not reported). These results, along with the H1 results, are consistent with the idea that the SG&A expense category of new firms increasingly includes immediately expensed investment outlays.

4.3.1. Additional tests using the cash components of revenues and expenses

I estimate matching in Eq. (1) by using the cash components of revenues and expenses. The second column of Panel A in Table 4 shows declining matching of 0.85, 0.83, 0.71, 0.72, and 0.44 across the successive waves. This result shows that the decline in matching of total expenses is strongly associated with developments in the underlying revenue–expense relation. In this respect, my conclusion differs from Dichev and Tang (2008), who rule out real developments as a reason for the decline in matching over time.

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[12] Similarly, I find no significant differences between the 1980s and 1990s waves in most of the tests described later. For brevity, I do not repeat this point.

[13] I estimate a "trend rate" (γ_2) using 40 annual averages of the firm population and the following equation: $AverageAnnualAttribute_t = \gamma_1 + \gamma_2 \times t + \varepsilon_t$. I find a negative trend rate for SG&A matching.

[14] To examine "economically substantial firms," Dichev and Tang (2008) and Donelson et al. (2011) select a sample of one thousand firms with the largest assets. Their tests require each firm to have at least 12 years of prior data. Their selection criteria result in a sample with an average listed age of 26 years. Thus, their sample largely excludes new firms.

Table 4
The average revenue–expense matching, earnings volatility, and earnings relevance of the successive listing cohorts.

Panel A presents the average measures of earnings quality (EQ) of the successive listing cohorts. All of the firms are divided into five listing cohorts in the following steps. The first year in which a firm's data are available in Compustat is referred to as the "listing year." All of the firms with a listing year before 1970 are classified as "seasoned firms." The remaining firms are classified as "new firms." All of the cohorts listed in a common decade are referred to as a "wave" of new firms. Consequently, all of the firms are divided into seasoned firms or a wave from the 1970s, 1980s, 1990s, or 2000s. The EQ measures are first calculated on a wave-year basis by using the methods described in Appendix A. These methods result in 40 annual observations for the seasoned-firm category (1970–2009), 40 annual observations for the 1970s wave (1970–2009), 30 annual observations for the 1980s wave (1980–2009), 20 annual observations for the 1990s wave (1990–2009), and ten annual observations for the 2000s wave (2000–2009) for each attribute. Volatility has one fewer observation per wave. The overall average EQ measure of a listing cohort is calculated by averaging all of its annual estimates.

Panel A: The average earnings quality of the successive listing cohorts

Listing cohort	Matching	Matching of cash components of revenues and expenses	Expense volatility	Revenue volatility	Earnings volatility	Volatility of cash flow from operations	Earnings relevance (%)
Seasoned firms	1.00	0.85	0.13	0.14	0.03	0.06	15.26
1970s wave	0.96	0.83	0.20	0.20	0.07	0.10	10.73
1980s wave	0.80	0.71	0.27	0.22	0.15	0.18	5.00
1990s wave	0.77	0.72	0.27	0.22	0.16	0.17	4.79
2000s wave	0.38	0.44	0.47	0.25	0.37	0.38	2.41

Differences in the earnings qualities of the successive listing cohorts after controlling for overall time trends.

Panel B examines whether the measures of earnings quality (EQ) differ across successive listing cohorts after controlling for overall time trends. All of the firms are divided into five listing cohorts in the following steps. The first year in which a firm's data are available in Compustat is referred to as the "listing year." All of the firms with a listing year before 1970 are classified as "seasoned firms." The remaining firms are classified as "new firms." All of the cohorts listed in a common decade are referred to as a "wave" of new firms. Consequently, all of the firms are divided into seasoned firms or a wave from the 1970s, 1980s, 1990s, or 2000s. Matching and earnings relevance are calculated on a wave-year basis by using the methods described in Appendix A. Then, the following regression is estimated by using 140 wave-year observations, comprising 40 annual observations for the seasoned-firm category (1970–2009), 40 annual observations for the 1970s wave (1970–2009), 30 annual observations for the 1980s wave (1980–2009), 20 annual observations for the 1990s wave (1990–2009), and ten annual observations for the 2000s wave (2000–2009).

$$EQMeasure_{Wave,year} = \beta_1 + \beta_2 \times FiscalYear + \gamma_1 \times DummyListYear1970\_79 + \gamma_2 \times DummyListYear1980\_89 + \gamma_3 \times DummyListYear1990\_99 + \gamma_4 \times DummyListYear2000\_09 + \varepsilon_{Wave,year},$$

where the dummy variables *DummyListYear1970_79*, *DummyListYear1980_89*, *DummyListYear1990_99*, and *DummyListYear2000_09* take the value of one for the wave-year observations of the 1970s, 1980s, 1990s, and 2000s waves, respectively, and zero otherwise. Because a dummy variable for the seasoned-firm observations is not included in the above regression, they form the base case.

Panel B: Differences in the earnings qualities of the successive listing cohorts.

	Matching		Earnings relevance	
	Estimate	*t*-Statistic	Estimate	*t*-Statistic
Intercept	14.152	6.87***	5.971	8.17***
Fiscal Year × *1,000*	−6.612	−6.38***	−2.921	−7.95***
DummyListYear1970_79	−0.039	−1.47	−0.046	−4.83***
DummyListYear1980_89	−0.163	−5.50***	−0.088	−8.58***
DummyListYear1990_99	−0.157	−4.54***	−0.073	−6.32***
DummyListYear2000_09	−0.516	−11.34**	−0.085	−5.43***
N		140		140
F-value		58***		47***
Adjusted *R*-square (%)		67.28		61.83
F-tests		*p*-Value		*p*-Value
Average seasoned firms = 1970s wave (γ_1)		0.001		< 0.001
Average 1970s wave = 1980s wave ($\gamma_1 = \gamma_2$)		< 0.001		< 0.001
Average 1980s wave = 1990s wave ($\gamma_2 = \gamma_3$)		0.872		0.199
Average 1990s wave = 2000s wave ($\gamma_3 = \gamma_4$)		< 0.001		0.478

*** and ** indicate statistical significance (two-sided) at the 1% and 5% levels, respectively.

Differences in the earnings volatilities of the successive listing cohorts after controlling for overall time trends.

Panel C examines whether the volatilities of revenues, expenses, and earnings differ across successive listing cohorts after controlling for overall time trends. All of the firms are divided into five listing cohorts in the following steps. The first year in which a firm's data are available in Compustat is referred to as the "listing year." All of the firms with a listing year before 1970 are classified as "seasoned firms." The remaining firms are classified as "new firms." All of the cohorts listed in a common decade are referred to as a "wave" of new firms. Consequently, all of the firms are divided into seasoned firms or a wave from the 1970s, 1980s, 1990s, or 2000s. Volatility is calculated on a wave-year basis by using the methods described in Appendix A. Then, the following regression is estimated by using 135 wave-year observations, comprising 40 annual observations for the seasoned-firm category (1970–2009), 39 annual observations for 1970s wave

Table 4 (*continued*)

(1971–2009), 29 annual observations for 1980s wave (1981–2009), 19 annual observations for 1990s wave (1991–2009), and nine annual observations for 2000s wave (2001–2009):

$$Volatility_{Wave,year} = \beta_1 + \beta_2 \times FiscalYear + \gamma_1 \times DummyListYear1970\_79 + \gamma_2 \times DummyListYear1980\_89 + \gamma_3 \times DummyListYear1990\_99 + \gamma_4 \times DummyListYear2000\_09 + \varepsilon_{Wave,year},$$

where the dummy variables *DummyListYear1970_79*, *DummyListYear1980_89*, *DummyListYear1990_99*, and *DummyListYear2000_09* take the value of one for the wave-year observations of the 1970s, 1980s, 1990s, and 2000s waves, respectively, and zero otherwise. Because a dummy variable for the seasoned-firm observations is not included in the above regression, they form the base case.

Panel C: Differences in the earnings volatilities of the successive listing cohorts

	Revenue volatility		Expense volatility		Earnings volatility	
	Estimate	*t*-Statistic	Estimate	*t*-Statistic	Estimate	*t*-Statistic
Intercept	2.891	9.30***	−0.884	−1.59	−4.391	−8.17***
Fiscal Year × 1,000	−1.382	−8.85***	0.512	1.83*	2.221	8.23***
DummyListYear1970_79	0.061	15.49***	0.067	9.59***	0.035	5.19***
DummyListYear1980_89	0.085	19.51***	0.131	16.68***	0.107	14.20***
DummyListYear1990_99	0.092	17.75***	0.128	13.79***	0.103	11.40***
DummyListYear2000_09	0.132	18.35***	0.329	25.70***	0.302	24.41***
N		135		135		135
F-value		126***		193***		223***
Adjusted *R*-square (%)		82.64		87.94		89.94
F-tests		*p*-Value		*p*-Value		*p*-Value
Average seasoned firms = 1970s wave (γ_1)		< 0.001		< 0.001		< 0.001
Average 1970s wave = 1980s wave ($\gamma_1 = \gamma_2$)		< 0.001		< 0.001		< 0.001
Average 1980s wave = 1990s wave ($\gamma_2 = \gamma_3$)		0.171		0.839		0.379
Average 1990s wave = 2000s wave ($\gamma_3 = \gamma_4$)		< 0.001		< 0.001		< 0.001

* and *** indicate statistical significance (two-sided) at the 10% and 1% levels, respectively.

4.4. H2B: successive waves' increasing earnings volatility

The successive waves exhibit increasing revenue volatilities of 0.14, 0.20, 0.22, 0.22, and 0.25 (the fourth column of Panel A in Table 4). This pattern arguably reflects increases in underlying business risks (Brown and Kapadia, 2007) or the higher uncertainty of the benefits associated with intangible investments (Kothari et al., 2002). In addition, the successive waves exhibit increasing expense volatility, as discussed in Section 4.2. These developments, along with a decline in matching, should increase earnings volatility. Specifically, earnings volatility should increase because it equals the sum of the expense and revenue volatilities minus twice their covariance. The fifth column of Panel A in Table 4 shows that the successive waves display increasing earnings volatility of 0.03, 0.07, 0.15, 0.16, and 0.37. And the last column of Panel C in Table 4 shows similar patterns despite controlling for overall time trends.

4.4.1. Additional tests on the volatility of operating cash flow

The sixth column of Panel A in Table 4 shows an increase in the volatility of operating cash flows across successive waves of 0.06, 0.10, 0.18, 0.17, and 0.38. In unreported tests, I find that more than 95% of the increase over time in average earnings volatility is explained by the increase in average cash flow volatility. This inference differs from Givoly and Hayn (2000, p. 313). Their Fig. 3, based on a constant sample of firms, shows a large increase in earnings volatility over time but shows no corresponding increase in the volatility of operating cash flows.[15] Similarly, Dichev and Tang (2008, p. 1452) find large changes in the time-series properties of earnings but no significant change in the time-series properties of operating cash flows. Thus, by examining a changing sample of firms that represent the changing firm population, my study extends both of these studies. I show that the change over time in the properties of underlying cash flows is a significant factor for the observed change in the time-series properties of earnings.

4.5. H2C: successive waves' decreasing earning relevance

Relevance is a widely employed measure of earnings quality. The correlational tests in Section 3.3.2 show that relevance improves with matching but declines with earnings volatility. Moreover, in H2A and H2B tests, I find significant declines in

[15] However, they do not test the significance of temporal changes in cash flow volatility. They find that the principal reason for the increase in earnings volatility is the increase in the volatility of non-operating accruals that results from the increase in special items.

Table 5
Disaggregation of the changes over time in the average measures of earnings quality.

This table examines the contribution of the increases in the numerical percentage of "new" firms in the firm population and their distinctive attributes to the changes over time in the average measures of earnings quality (EQ). All of the EQ measures are calculated on an annual basis for the "new-firm" and "seasoned-firm" segments by using the methods described in Appendix A. All of the firms are divided into these two segments in the following steps. The first year in which a firm's data are available in Compustat is referred to as the "listing year." All of the firms with a listing year before 1970 are classified as "seasoned firms." The remaining firms are classified as "new firms." The average EQ measure in a year should equal the weighted average of EQ measures of the new and seasoned firm segments. As described in Appendix B, the changes in average EQ measure from the early 1970s to the late 2000s should be:

$$\begin{aligned} EQ_{Population,Late2000s} - EQ_{Population,Early1970s} = {} & Percent_{SeasonedFirms,Early1970s} \times (EQ_{SeasonedFirms,Late2000s} - EQ_{SeasonedFirms,Early1970s}) \quad \text{[first term]} \\ & + Percent_{NewFirms,Early1970s} \times (EQ_{NewFirms,Late2000s} - EQ_{NewFirms,Early1970s}) \quad \text{[second} - \text{A term]} \\ & + (Percent_{NewFirms,Late2000s} - Percent_{NewFirms,Early1970s}) \times (EQ_{NewFirms,Late2000s} - EQ_{SeasonedFirms,Late2000s}), \quad \text{[second} - \text{B term]} \end{aligned}$$

where the early 1970s and the late 2000s refer to the years 1970–1974 and 2005–2009, respectively, and the percentages of the new-firm segment in the early 1970s and the late 2000s equal 24.01% and 91.53%, respectively. The "seasoned-firm effect" measures the contribution of changes in the EQ measures of the seasoned-firm segment, holding its percentage in the firm population constant at the early 1970s level. This effect is measured by the first term in the equation. The "new-list" effect represents the combined effect of the new-firm segment's distinctive EQ measures as well as its percentage increase in the firm population. The sum of the second-A term and the second-B term represents the new-list effect. The trend rate is measured by $\gamma_2 \times 1{,}000$ where γ_2 is obtained from the following regression estimated by using 40 annual observations from 1970 to 2009: $EQMeasure_t = \gamma_1 + \gamma_2 \times t + \varepsilon_t$.

	EQ measures		
	Earnings relevance	Matching	Earnings volatility
Seasoned-firm segment			
Attribute (early 1970s)	20.12%	1.049	0.022
Attribute (late 2000s)	14.40%	0.935	0.040
Percent change in attribute	−28.43	−10.84	79.21
New-firm segment			
Attribute (early 1970s)	20.42%	1.052	0.038
Attribute (late 2000s)	2.56%	0.591	0.230
Percent change in attribute	−87.44	−43.83	513.34
Percent difference in attributes of new- and seasoned-firm segments			
Early 1970s	1.47	0.32	68.34
Late 2000s	−82.19	−36.80	476.12
Trend rates			
Seasoned-firm segment	−1.83	−2.83	0.62
New-firm segment	−4.07	−13.40	5.73
Difference	−2.24	−10.57	5.11
(*p*-value)	(< 0.01)	(< 0.01)	(< 0.01)
Percent contribution to changes in the average attributes of the firm population			
First term (seasoned-firm effect)	26.15	20.11	7.13
Second-A term	25.78	25.78	24.59
Second-B term	48.07	54.11	68.28
New-list effect	73.85	79.89	92.87

matching and significant increases in earnings volatility for the successive waves. Therefore, not surprisingly, the seventh column of Panel A in Table 4 shows that successive waves exhibit decreasing earnings relevance of 15.26%, 10.73%, 5.00%, 4.79%, and 2.41%. The relevance of the latest wave is 84% lower than that of the seasoned firms. This result shows that the extent to which the "earnings of the reporting period reflect the information used by the market in forming prices during that period" (Easton et al., 1991, p. 120) declines with new waves.

To control for overall time trends, I estimate Eq. (4) with relevance as the dependent variable. The results presented in the second column of Panel B in Table 4 show that the 1970s wave has significantly lower relevance than the seasoned firms and that the 1980s wave has significantly lower relevance than the 1970s wave. Yet the earnings relevance measures of the last three waves (1980s, 1990s, and 2000s) do not significantly differ from each other. Nevertheless, all four waves show dramatically lower relevance than that of seasoned firms.

I also estimate a regression of stock returns on the levels of, and changes in, operating cash flows [instead of earnings in Eq. (3)]. In unreported tests, I find a declining pattern in the adjusted *R*-squares of the modified Eq. (3) across the successive waves. This finding suggests that the decline in relevance of the successive waves is at least partly due to the decline in the relation between stock returns and concurrent cash flows.

4.6. Differences in trends of EQs of the new-firm and the seasoned-firm segments

The H2 tests show that successive waves display declining EQ measures even after controlling for overall time trends. As a result, each new wave's arrival should reduce the EQ measures of the new-firm segment. Also, the EQ measures of the new-firm segment should decline faster than that of the seasoned-firm segment. Table 5 shows that for each of the three EQ measures, the magnitude of the trend rate (calculation described in footnote 13) is significantly higher for the new-firm segment than for the seasoned-firm segment. As a result, over the sample period, the new-firm segment's relevance declined from 20.4% to just 2.6%, or by 87%. The seasoned-firm segment's relevance also declined, but less dramatically, from 20.1% to 14.4%. Furthermore, the new-firm segment's matching declined from 1.05 to 0.59. In contrast, the seasoned-firm segment's matching declined much less, from 1.05 to 0.94.[16] In addition, the earnings volatility increased more significantly for the new-firm segment. Consequently, at the end of the study period, relative to the seasoned-firm segment, the new-firm segment's earnings relevance was lower by 82%, matching was lower by 37%, and earnings volatility was higher by 476%.

4.6.1. The relative contributions of the new-list and seasoned-firm effects to changes in average EQ measures

The firm populations' average EQ measure equals the weighted average of the new and seasoned firms' EQ measures:

$$EQ_{Population} = Percent_{SFirms} \times EQ_{SFirms} + (1 - Percent_{SFirms}) \times EQ_{NFirms}, \tag{5}$$

where *EQ* equals the earnings quality measure, *SFirms* equals the seasoned firms, and *NFirms* equals the new firms.

Thus, as described in Appendix B, the changes in the average EQ measures from the early 1970s (i.e., 1970–1974) to the late 2000s (i.e., 2005–2009) can be expressed as follows[17]:

$$\begin{aligned} EQ_{Population,Late2000s} - EQ_{Population,Early1970s} &= [Percent_{SFirms,Early1970s} \times (EQ_{SFirms,Late2000s} - EQ_{SFirms,Early1970s})] \\ &+ [Percent_{NFirms,Early1970s} \times (EQ_{NFirms,Late2000s} - EQ_{NFirms,Early1970s}) + (Percent_{NFirms,Late2000s} - Percent_{NFirms,Early1970s}) \\ &\times (EQ_{NFirms,Late2000s} - EQ_{SFirms,Late2000s})] \end{aligned} \tag{6}$$

I refer to the first term in the square brackets as the seasoned-firm effect. This term measures the contribution of the changes in EQ measures of the seasoned-firm segment, holding its percentage in the firm population constant. I refer to the second term in square brackets as the new-list effect. This term represents the combined effect of the new-firm segment's distinctive EQ measures and the increase in their numerical percentage in the firm population. I then calculate the percentage contributions of the seasoned-firm and new-list effects to changes in the average EQ measures from the early 1970s to the late 2000s.

Table 5 shows that the new-list effect accounts for 73.9%, 80.0%, and 92.9% of the temporal changes in average earnings relevance, matching, and volatility, respectively. The seasoned-firm effect accounts for the remaining 26.1%, 20.0%, and 7.1%, respectively. Hence, I conclude that the bulk of the changes over time in the EQ measures reflects the new-list effect. This is my main contribution to the literature. My conclusion differs from that of Lev and Zarowin (1999, p. 358), who conclude that the declining returns-earnings association is not the result of new firms joining the sample. This difference occurs because I include firms listed in the late 1990s and the first decade of the 2000s that Lev and Zarowin (1999) do not examine. These firms display significantly lower EQ measures than do seasoned firms.[18] In addition, my conclusion differs from that of Dichev and Tang (2008, p. 1426), who conclude that the decline in matching is not because of changes in the firm sample.

4.7. Factors related to the new-list effect

I next examine the principal reasons for the widening gap between the EQ measures of the new- and the seasoned-firm segments. I estimate the following univariate regression with factors that potentially affect the EQ measures as explanatory variables:

$$DifferenceEarningsQuality_{Year} = \alpha + \gamma_1 \times DifferenceAttribute_{Year} + \varepsilon_{Year} \tag{7}$$

I use the differences between annual cross-sectional averages of the attributes of the new- and seasoned-firm segments as dependent and independent variables. Specifically, I use one of the annual differences in relevance, matching, or volatility as the dependent variable and one of the annual difference in special items (Elliott and Hanna, 1996), revenue volatility (Hribar and Nichols, 2007), market-to-book ratio, or SG&A intensity as the independent variable. Of these factors, market-to-book ratio and SG&A intensity represent intangible intensity. Accordingly, I use 40 annual observations (1970–2009) to estimate each of the 12 [3 (earnings qualities) $\times$ 4 (explanatory variables)] univariate regressions.

The results of these 12 regressions, presented in Panels A–D of Table 6, show that the *R*-squares of the regressions based on intangible intensity, ranging from 25% to 71%, are the highest. These results indicate that the widening gap between the intangible intensities of the new- and seasoned-firm segments is the most important factor in explaining the widening gap

[16] The core expenses of the seasoned firms remain highly correlated with their current revenues. And the matching for the seasoned firms declines largely due to increases in special items (Donelson et al., 2011).

[17] The early 1970s refers to the five-year period from 1970 to 1974. Similarly, the late 2000s refer to the five-year period from 2005 to 2009. I examine changes from the early 1970s to the late 2000s instead of from 1970 to 2009 to control for temporary year-to-year variations. I reach similar conclusions by examining changes from 1970 to 2009.

[18] The Lev and Zarowin (1999) conclusion is based on findings of significant declines in the relevance of both constant and total firm samples and no significantly higher trend rate in the total sample relative to the constant sample. Nevertheless, the data presented in their Table 1 show that the new firms have lower relevance than the old firms. More important, by extending the Lev and Zarowin (1999) study period to 2009, I find that the difference between the trend rates of the two samples becomes significant.

Table 6
Factors associated with the new-list effect.

This table examines the principal reasons for the widening gap between the average earnings quality (EQ) measures of the "new-firm" and the "seasoned-firm" segments. All of the firms are divided into these two segments in the following steps. The first year in which a firm's data are available in Compustat is referred to as the "listing year." All of the firms with a listing year before 1970 are classified as seasoned firms. The remaining firms are classified as new firms. The following univariate regression is estimated by using one of the factors that potentially affect the EQ measures as an explanatory variable:

$$DifferenceEQ_{Year} = \alpha + \gamma_1 \times DifferenceAttribute_{Year} + \varepsilon_{Year}$$

In this equation, the dependent variable is the annual difference between one of the EQ measures (earnings relevance, matching, or earnings volatility) of the new- and seasoned-firm segments. And the independent variable is one of the annual differences between the new- and seasoned-firm segments' special items, revenue volatility, market-to-book ratio, or SG&A intensity. All of the variables are defined in Appendix A. Each regression is estimated using 40 annual observations (1970–2009).

Panel A: $DifferenceEQ_{Year} = \alpha + \gamma_1 \times DifferenceSpecialItems_{Year} + \varepsilon_{Year}$

	Annual differences					
$N=40$	Earnings relevance		Matching		Earnings volatility	
	Estimate	*t*-Statistic	Estimate	*t*-Statistic	Estimate	*t*-Statistic
Intercept	−0.063	−5.23***	−0.101	−3.84***	0.068	6.01***
DifferenceSpecialItems	0.041	–0.03	–4.934	–1.59	2.186	1.71*
F-value		2.92		17.92		2.92
Probability		0.97		0.12		0.09
Adjusted *R*-square (%)		−2.78		3.94		4.93

*** and * indicate statistical significance (two-sided) at the 1% and 5% levels, respectively.

Panel B: $DifferenceEQ_{Year} = \alpha + \gamma_1 \times DifferenceRevenueVolatility_{Year} + \varepsilon_{Year}$

	Annual differences					
$N=40$	Earnings relevance		Matching		Earnings volatility	
	Estimate	*t*-Statistic	Estimate	*t*-Statistic	Estimate	*t*-Statistic
Intercept	0.087	1.92*	0.146	1.34	−0.100	−2.44**
DifferenceRevenueVolatility	−1.988	−3.37***	–3.573	−2.51**	2.361	4.43***
F-value		11.33		17.92		19.61
Probability		< 0.01		0.01		< 0.01
Adjusted *R*-square (%)		21.83		12.52		33.46

***, **, and * indicate statistical significance (two-sided) at the 1%, 5%, and 10% levels, respectively.

Panel C: $DifferenceEQ_{Year} = \alpha + \gamma_1 \times DifferenceM\text{-}BRatio_{Year} + \varepsilon_{Year}$

	Annual differences					
$N=40$	Earnings relevance		Matching		Earnings volatility	
	Estimate	*t*-Statistic	Estimate	*t*-Statistic	Estimate	*t*-Statistic
Intercept	–0.006	−0.40	0.011	0.30	0.010	0.71
DifferenceM-BRatio	−0.079	−3.38***	–0.189	−4.18***	0.095	5.39***
F-value		15.06		17.45		18.63
Probability		< 0.01		< 0.01		< 0.01
Adjusted *R*-square (%)		27.54		30.77		43.16

*** indicates statistical significance (two-sided) at the 1% level.

Panel D: $DifferenceEQ_{Year} = \alpha + \gamma_1 \times DifferenceSG\&A\text{-}Intensity_{Year} + \varepsilon_{Year}$

	Annual differences					
$N=40$	Earnings relevance		Matching		Earnings volatility	
	Estimate	*t*-Statistic	Estimate	*t*-Statistic	Estimate	*t*-Statistic
Intercept	0.023	0.93	0.166	3.89***	−0.058	−3.83***
DifferenceSG&A-Intensity	−0.881	−3.67***	–2.962	−7.23***	1.399	9.53***

Table 6 (*continued*)

Panel D: $DifferenceEQ_{Year} = \alpha + \gamma_1 \times DifferenceSG\&A\text{-}Intensity_{Year} + \varepsilon_{Year}$

$N=40$	Annual differences					
	Earnings relevance		Matching		Earnings volatility	
	Estimate	*t*-Statistic	Estimate	*t*-Statistic	Estimate	*t*-Statistic
F-value		13.49		52.53		90.77
Probability		< 0.01		< 0.01		< 0.01
Adjusted *R*-square (%)		25.23		58.12		70.81

***Indicates statistical significance (two-sided) at 1% level.

This panel uses the partial *R*-square method (Wold, 1966) to examine the relative contributions of the principal reasons for the widening gap between the average EQ measures of the new-firm and the seasoned-firm segments. The market-to-book ratio is excluded from the following multivariate regression because it is highly correlated with SG&A intensity.

Panel E: $DifferenceEQ_{Year} = \alpha + \gamma_1 \times DifferenceSpecialItems_{Year} + \gamma_2 \times DifferenceRevenueVolatility_{Year} + \gamma_3 \times DifferenceSG\&A\text{-}Intensity_{Year} + \varepsilon_{Year}$

$N=40$	Annual differences					
	Earnings relevance		Matching		Earnings volatility	
	Estimate	Partial *R*-square	Estimate	Partial *R*-square	Estimate	Partial *R*-square
Intercept	0.071	–	0.029	–	−0.057	–
DifferenceSpecialItems	1.715	0.00%	0.773	6.53%	−0.291	7.49%
DifferenceRevenueVolatility	−0.899	8.83%	2.971**	11.56%	−0.049	30.08%
DifferenceSG&A-Intensity	−0.745**	25.16%	−3.893***	46.36%	1.434***	34.13%
R-square† (%)		33.99		64.45		71.70
Adjusted *R*-square (%)		28.16		61.29		69.23
F-value		5.84		20.53		28.75
Probability		< 0.01		< 0.01		< 0.01

*** and ** indicate statistical significance (two-sided) at the 1% and 5% levels, respectively.
†Equals the sum of the partial *R*-squares.

between their EQ measures. I find similar results by using R&D as an alternative measure of intangibles (results not reported).

I also use the partial *R*-square method (Wold, 1966) to examine the relative contributions of the principal reasons for the widening gap between the EQ measures of the new- and the seasoned-firm segments. I estimate the following multivariate regression[19]:

$$DifferenceEarningsQuality_{Year} = \alpha + \gamma_1 \times DifferenceSpecialItems_{Year} + \gamma_2 \times DifferenceRevenueVolatility_{Year} + \gamma_3 \times DifferenceSG\&A - Intensity_{Year} + \varepsilon_{Year} \tag{8}$$

Results presented in Panel E of Table 6 show that the partial *R*-squares of SG&A intensity are the highest. Results in this section, along with the results in Section 4.6.1, are consistent with the idea that the increases in intangible intensity of the new-firm segment along with its percentage increase in the listed firm population are the principal factors for the observed decline in the average EQ measures.

5. Concluding remarks

This study shows that successive cohorts of newly listed firms since 1970 exhibit progressively lower EQ measures. One of the principal reasons for this development is the successive cohorts' increasing intangible intensity, which affects the firms' business performance and their financial reports. Specifically, successive cohorts display increasing volatility of both revenues and cash flows, arguably because of high uncertainty about the benefits of intangible investments. Further, successive cohorts display decreasing matching and increasing expense volatility, mainly because of the immediate expensing of intangible investments. The increases in revenue and expense volatilities, in conjunction with the decline in

[19] The partial *R*-square (or coefficient of partial determination) measures the marginal contribution of one explanatory variable when all other variables are included in the model. I do not include market-to-book ratio in this regression because it is highly correlated with SG&A intensity.

matching, heighten earnings volatility. The increased earnings volatility makes earnings less useful for predicting a firm's future performance. Hence, successive cohorts show a declining relevance of earnings.

Consequently, each new cohort's arrival lowers the average EQ measures of the firm population. And the cumulative addition of new cohorts explains approximately three-quarters of the changes in EQ measures since 1970. Accordingly, I conclude that the main reason for the observed trend in average EQ measures is not the changes in the earnings quality of the seasoned firms but rather the inclusion of new firms in the firm population. Further, I find similar trends by using the cash components of revenues, expenses, and earnings, which are less likely to be affected by changes in GAAP and more likely to reflect changes in the nature of the underlying transactions. Accordingly, I conclude that the observed trend in EQ measures is strongly related to changes in the business activities of the listed firms.

Appendix A. Definitions of variables

The firm population consists of all nonfinancial firms that in a sample formation year have assets, earnings, and revenue data from the previous two years, the current year, and the next year; and stock-price data from the end of the previous and current years.

The corresponding data items in the Compustat annual database are listed in capital letters.

Total Assets	=	AT
Revenues	=	SALE, scaled by average Total Assets for the year
Earnings	=	IB, scaled by average Total Assets for the year
Total Expenses	=	(SALE – IB), scaled by average Total Assets for the year
COGS	=	Cost of Goods Sold (COGS), scaled by average Total Assets for the year
SG&A	=	Selling, General, and Administrative expenses (XSGA), scaled by average Total Assets for the year
Noncore Expenses	=	Total Expenses – (*COGS*+*SG&A*)
Market-to-Book Ratio	=	[Market Value of Equity (Price {PRCC_F} × Number of Shares Outstanding {CSHO})+Total Liabilities [Total Assets − Shareholder Equity {CEQ}]]/Total Assets.
Accruals	=	[Change in Current Assets (ACT) − Change in Cash (CHE) − Change in Current Liabilities (LCT) − Change in Tax Payable (TXP) − Depreciation and Amortization (DP)], scaled by average Total Assets for the year
Revenue Accruals	=	[Change in Accounts Receivable (AR) − Change in Deferred Revenue (DRC+DRLT)], scaled by average Total Assets for the year
Expense Accruals	=	Accruals − Revenue Accruals
Cash Flow from Operations (*CFO*)	=	Earnings − Accruals
Cash Component of Revenues	=	Revenues − Revenue Accruals
Cash Component of Expenses	=	Total Expenses − Expense Accruals
Attributes		
SG&A Intensity	=	Selling, General, and Administrative expenses (XSGA)/Total Expenses
COGS Intensity	=	Cost of Goods Sold (COGS)/Total Expenses
Noncore Intensity	=	1 − (*SG&A* Intensity + *COGS* Intensity)
R&D Intensity	=	Research and Development Expenditures (XRD)/Total Expenses
Matching and Forward Association	=	The following regression is estimated on an annual cross-sectional basis for each wave-year: $Revenue_t = \beta_1 + \beta_2 \times TotalExpense_{t-1} + \beta_3 \times TotalExpense_t + \beta_4 \times TotalExpense_{t+1} + \varepsilon_t$. Forward Association and Matching are measured by β_2 and β_3, respectively.
Matching of SG&A	=	The following regression is estimated on an annual cross-sectional basis for each wave-year: $Revenue_{i,t} = \beta_1 + \beta_2 \times TotalExpense_{t-1} + \beta_3 \times COGS_{i,t} + \beta_4 \times SG\&A_{i,t} + \beta_5 \times NoncoreExpenses_{i,t} + \beta_6 \times TotalExpenses_{i,t+1} + \varepsilon_{i,t}$ Matching of *SG&A* is measured by β_4.
Volatility of *SG&A*, Revenues, Expenses, Earnings, and *CFO*	=	Standard deviation of *SG&A*, Revenues, Expenses, Earnings, and *CFO*, respectively, for the four-year rolling windows (years $t-2$ through $t+1$)
Relevance	=	Adjusted *R*-square of the following regression, estimated on an annual cross-sectional basis for each wave-year: $RET_{i,t} = \beta_{1,t} + \beta_{2,t} \times \Delta Earnings_{i,t} + \beta_{3,t} \times Earnings_{i,t} + \varepsilon_{i,t}$ *RET* is [(End-of-Year Share Price {PRCC_F}/Adjustment Factor {AJEX}+Dividend per Share {DVPSP_F}/Adjustment Factor − Beginning-of-Year Share Price/Beginning-of-Year Adjustment Factor)/(Beginning-of-Year Share Price/Beginning-of-Year Adjustment Factor)]. Earnings and change in Earnings are scaled by average Total Assets.
EQ measures	=	Earnings Volatility, Revenue–Expense Matching, and Earnings Volatility.
Firm category		
Listing year	=	First year in which the firm has valid data in Compustat.
Seasoned firms	=	Firms whose listing year is before 1970.
New firms	=	Firms that are not Seasoned firms.
Listing cohorts	=	All of the cohorts listed in a common decade are referred to as a "wave" of New firms. Consequently, all of the firms are divided into Seasoned firms or a wave from the 1970s, 1980s, 1990s, or 2000s.

Dummy variables for waves	=	Dummy variables *DummyListYear1970_79*, *DummyListYear1980_89*, *DummyListYear1990_99*, and *DummyListYear2000_09*, take the value of one for the wave-year observations of the 1970s, 1980s, 1990s, and 2000s waves, respectively, and zero otherwise.
Industry	=	All of the firms are classified by the Fama–French 48-industry method. Four industries representing the finance firms and one "almost nothing" category are excluded, leaving 43 industries.
Recency	=	Wave-order values of 1, 2, 3, 4, and 5 are assigned to the Seasoned firms, and the firms listed in the 1970s, 1980s, 1990s, and the first decade of 2000s, respectively. An industry's average recency is calculated by averaging the wave-order values of its pooled firm-year observations.

Notes:

- All variables are winsorized at the 1st and 99th percentiles.
- Industry tests (Table 2)
  - The average attribute for an industry, measured by a proportion or a volatility, is first calculated on a firm-year basis and then averaged across all of that industry's pooled observations. Other attributes (relevance and matching) are estimated by pooled panel-data regressions by industry. These methods results in 43 industry observations for each attribute.
- Time-series tests (Tables 3–6)
  - An attribute for a wave-year, measured by a proportion or a volatility, is first calculated on a firm-year basis and then averaged across all of the cross-sectional observations in that wave-year. Other attributes (relevance and matching) are estimated by cross-sectional regressions by wave-year. These methods result in 140 wave-year observations for each attribute, comprising 40 observations for seasoned firms (1970–2009), 40 observations for the 1970s wave (1970–2009), 30 observations for the 1980s wave (1980–2009), 20 observations for the 1990s wave (1990–2009), and observations for the 2000s wave (2000–2009). Volatility has one less observation per wave. The overall average attribute of a listing cohort is calculated by averaging all of its annual wave-year attributes.
  - The annual attribute of the new-firm segment is calculated by averaging the wave-year attributes of the 1970s, 1980s, 1990s, and 2000s waves.
  - Years 1970–1974 and 2005–2009 are referred to as the early 1970s and the late 2000s, respectively.

Appendix B. Contributions of the new-list and seasoned-firm effects to changes in EQ measures

The observed earnings quality of the firm population equals the weighted average of the EQ measures of the new- and the seasoned-firm segments as described below:

$$EQ_{Population,T1} = WT_{SF,T1} \times EQ_{SF,T1} + WT_{NF,T1} \times EQ_{NF,T1} \tag{B.1}$$

where EQ=EQ measures, WT=percentage in firm population, SF=seasoned firms, NF=new firms, T1=early 1970s (1970–1974), and T2=late 2000s (2005–2009).

$$EQ_{Population,T2} = WT_{SF,T2} \times EQ_{SF,T2} + WT_{NF,T2} \times EQ_{NF,T2} \tag{B.2}$$

because

$$WT_{SF,T2} = WT_{SF,T1} + [WT_{SF,T2} - WT_{SF,T1}] \tag{B.3}$$

and

$$WT_{NF,T2} = WT_{NF,T1} + [WT_{NF,T2} - WT_{NF,T1}]. \tag{B.4}$$

Eq. (B.2) can be written as

$$EQ_{Population,T2} = (WT_{SF,T1} + [WT_{SF,T2} - WT_{SF,T1}]) \times EQ_{SF,T2} + (WT_{NF,T1} + [WT_{NF,T2} - WT_{NF,T1}]) \times EQ_{NF,T2} \tag{B.5}$$

$$= WT_{SF,T1} \times EQ_{SF,T2} + WT_{NF,T1} \times EQ_{NF,T2} + (WT_{SF,T2} - WT_{SF,T1}) \times EQ_{SF,T2} + (WT_{NF,T2} - WT_{NF,T1}) \times EQ_{NF,T2} \tag{B.6}$$

but

$$(WT_{SF,T2} - WT_{SF,T1}) = -1 \times (WT_{NF,T2} - WT_{NF,T1}). \tag{B.7}$$

Thus, (B6) can be expressed as

$$EQ_{Population,T2} = WT_{SF,T1} \times EQ_{SF,T2} + WT_{NF,T1} \times EQ_{NF,T2} + (WT_{NF,T2} - WT_{NF,T1}) \times (EQ_{NF,T2} - EQ_{SF,T2}). \tag{B.8}$$

Subtracting (B.1) from (B.8) gives

$$\begin{aligned} EQ_{Population,T2} - EQ_{Population,T1} = {} & WT_{SF,T1} \times (EQ_{SF,T2} - EQ_{SF,T1}) \quad \text{(first term)} \\ & + WT_{NF,T1} \times (EQ_{NF,T2} - EQ_{NF,T1}) \quad (second - A\ term) \\ & + (EQ_{NF,T2} - EQ_{SF,T2}) \times (WT_{NF,T2} - WT_{NF,T1}) \quad \text{(second} - \text{B term)} \end{aligned}$$

1. First term: Changes in the EQ measures of the seasoned-firm segment over time holding their percentage in the firm population constant. This term is referred to as the "seasoned-firm effect."
2. Second-A term: Changes in the EQ measures of the new-firm segment over time holding their percentage in the firm population constant.
3. Second-B term: Differences between the EQ measures of the new- and the seasoned-firm segments at the end of the study period $\times$ the percentage increase of the new-firm segment.

The sum of the second-A term and the second-B term is the "new-list" effect.

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