**A systematic problem in the detection of abnormal acts with industry-based models**

**Anup Srivastava**[†]

## ABSTRACT

Each new cohort of firms entering an industry uses higher amounts of intangible inputs in its business practice than do established firms. Also, firms tend to retain their initial business practices. Hence, when measured in a year, oldest and newest cohorts in each industry lie at the opposite ends of the spectrums of not just intangible intensity but also of the accounting and financial characteristics that are associated with production function. A researcher could misinterpret a large deviation in the characteristics of these cohorts from the industry median as an abnormal or manipulative act. I demonstrate this idea in a model that treats a below-median intangible expenditure as a real activity manipulation. I suggest parsimonious changes in industry-benchmarking models for future research.

Keywords: Industry classification; Industry peers; Intra-industry homogeneity; Real earnings management; Intangible investments; Matching.

JEL Classification: M41, M43, C12, C13, G32

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[†]E-mail: anup.srivastava@tuck.dartmouth.edu. Tuck School of Business, Dartmouth College, 100 Tuck Hall, Hanover, NH 03755-9000. Tel +1 603 646 3162.

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## 1. Introduction

The accuracy of the measurement of a firm's abnormal act rests on the accuracy of the estimated normal behavior. Researchers often use industry benchmarking models to estimate the firm's unobserved normal behavior by assuming a commonality in the characteristics of same-industry firms [intra-industry homogeneity (IIH) assumption.][1] This paper contributes to the economics, finance, and accounting literature by showing that successive cohorts of firms entering an industry systematically differ in their production functions as well as in their accounting and financial characteristics. I call it the "intra-industry listing-cohort" phenomenon. This phenomenon causes a significant violation of the IIH assumption and could lead to erroneous conclusions from a model that interprets a deviation from an industry median as an abnormal act. The paper also contributes to real earnings management (REM) literature by documenting and explaining four of its anomalies. Parsimonious changes are proposed for future research with industry-based models.

Management and economics literature posits that, since about 1970, new firms entering each industry have competed against established counterparts by disruptive innovations and by offering targeted services to customers.[2] Research also claims that innovation- and service-based competitive strategies require more intangible inputs [such as research and development (R&D), expert human capital, brand development, databases, and information technology] than cost-based competition. Based on these two ideas, I hypothesize that the more recently listed firms in a given industry use higher amounts of intangible inputs in their business practices than their older

[1] See Horrigan (1966), Morck et al. (1990), Jones (1991), Martin and McConnell (1992), Opler and Titman (1994), Denis and Denis (1995), Cascio et al. (1997), Healy et al. (1997), Cole and Mehran (1998), Morck and Nakamura (1999), Core et al. (1999), Dechow and Dichev (2002), Brickley (2003), Kaplan and Minton (2006), and Ahn et al. (2006).
[2] See Prahalad and Hamel (1990), Heskett et al. (1997), Shapiro and Varian (1998), Romer (1998), Payne and Frow (2005), Apte et al. (2008), Brickley and Zimmerman (2010), and Baumol and Schramm (2010).

counterparts. Prior studies find increases in intangible intensity of successive cohorts of listed firms, but they attribute it to the changing industry composition of public firms (Ritter and Welch 2002; Brown and Kapadia 2007; Srivastava 2014). I extend those studies by examining trends within each industry, an unexplored phenomenon.

I test my hypothesis by measuring intangible intensity with market-to-book ratio, R&D expenditures, and the proportion of total costs recognized in the selling, general, and administrative category of expenses (SG&A intensity). I measure all cohorts' characteristics at the same time, consistent with industry-benchmarking studies. I find progressively higher intangible intensities for successive cohorts within each industry. For example, R&D and SG&A intensity for firms listed after 2000 is at least two times higher than those for firms listed before 1970, both measured at the same time. Monotonic trends are also observed in the financial and economic characteristics that are associated with intangible intensity.[3] For example, each new cohort in a given industry displays higher sales growth, price-to-earnings ratio, likelihood of bankruptcy, incidence of losses, financial distress, and a need for external funds than did the predecessor cohort. Furthermore, in each industry and year, the oldest and newest cohorts lie at the opposite ends of the spectrums of three proxies of normal or non-manipulated characteristics: the cash component of earnings, the explained component of the performance-matched accrual model, and the explained component of the REM models.[4] Hence, I conclude that firms from successive cohorts in an industry differ monotonically in their innate attributes. I refer to this finding as the "intra-industry listing-cohort" phenomenon.

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[3] Investment in intangible assets is full of uncertainty (Holmstrom 1989; Kothari et al. 2002). Thus, intangible-intensive firms differ from other firms in their economic characteristics. See Smith and Watts (1992), Francis and Schipper (1999), Zingales (2000), Frank and Goyal (2003), Collins et al. (2007), Roychowdhury and Watts (2007), Armstrong et al. (2007), Skinner (2008), Srivastava (2014), and Zimmerman (2015).

[4] See Healy et al. (1992), Sloan (1996), Givoly and Hayn (2000), Dichev and Tang (2008), Kothari et al. (2005), and Roychowdhury (2006).

Firm life-cycle hypothesis and survivorship biases can explain these trends because, when compared in a common year, different cohorts have different ages, could be in different phases of their life cycles, and might use varying levels of intangible inputs (Anthony and Ramesh 1992; Dickinson 2011; Jovanovic and MacDonald 1994; Cohen et al. 2010). Also, the characteristics of firms that survive for a long time could differ from young firms. I control for the firm life-cycle and survivorship hypotheses by measuring all firms' characteristics at a fixed time interval after their listing years, when they should be in the same stage of their life cycle. For example, I measure characteristics of all pharmaceutical firms ten years after their listing years. I continue to find monotonic pattern at successive cohorts' common age. Also, the arrival of each new cohort shifts the average intangible intensity of an industry to a higher notch. These patterns cannot be explained by the life cycle or survivorship hypothesis. Instead, my findings indicate the progressively and persistently higher intangible intensity for successive cohorts. Each new cohort adopts a more intangible-intensive business practice by capitalizing on the additional technological progress achieved by the time of its formation. More important, it persists with its initial business practice despite subsequent progress because changing business models imposes significant disruptions and reorganization costs (Hambrick 1983; Yip 2004). "Organizational imprinting" and "innovator's dilemma" reinforce the ideas of persistence in firms' business models (Christensen 1997; Beckman and Burton 2008; Igami 2015).

Models that detect earnings management via discretionary accounting accruals have evolved in response to the findings of IIH violations (e.g., DeFond and Jiambalvo 1994; Dechow et al. 1995; Hribar and Collins 2002; Kothari et al. 2005). Implications of IIH violations are less well understood for REM models despite their growing popularity (Dechow et al. 2010; Siriviriyakul 2013; Cohen et al. 2015). REM models measure deviations in a firm's intangible outlays and production costs from industry normal by the residuals of the regressions of SG&A and cost of goods sold (COGS) on current revenues, respectively, estimated by industry and year. These deviations are interpreted as a curtailment of soft expense and a manipulation of the production schedule, respectively (Roychowdhury 2006). I refer to these regressions as the *SoftExpense* model and the *ProductionCost* model, respectively.

A critical assumption in REM models is that, absent real activities manipulation, the levels of COGS and SG&A as well as their correlations with current revenues are the same for all member firms in a given industry and year. These assumptions are systematically violated when multiple cohorts are included in an industry sample, which is a common occurrence.[5] The SG&A level is progressively higher, and SG&A's correlation with current revenues is progressively lower, for each new cohort in an industry. This pattern occurs because the intangible investments are largely expensed as incurred and reported in SG&A even when they do not produce current revenues (Dichev and Tang 2008; Banker et al. 2011; Eisfeldt and Papanikolaou 2013; Srivastava 2014). With the inclusion of each new cohort in an industry sample, the *SoftExpense* model becomes more misspecified and the model's explanatory power declines [e.g., the *R*-square is just 40% (Roychowdhury 2006, p. 349]. As a result, the regression residuals start reflecting innate, not manipulated, intangible expenses. Newer cohorts display large positive abnormal soft expenses while the older cohorts display large negative abnormal soft expenses. Notably, normal soft expenses show similar patterns. (Oldest and newest cohorts display lowest and highest levels, respectively.)

The inter-cohort variation of COGS is less of a concern in the *ProductionCost* model, because the recognition of production outlays is typically traced to revenues via COGS. Thus, the

[5] For example, on average, an industry sample drawn from Compustat for the year 2005 includes 8.0%, 6.5%, 13.6%, and 34.6%, 37.3% firms, respectively, listed before 1970 and listed in 1970s, 1980s, 1990s, and 2000s.

inter-cohort variation in innate COGS is absorbed by variation in revenues. [The *R*-square of the *ProductionCost* model is approximately 90% (Roychowdhury 2006, p. 349).] Hence, the *ProductionCost* model produces significantly smaller residuals than the *SoftExpense* model despite COGS being significantly larger than SG&A on average. Also, a researcher does not find large negative (positive) abnormal production costs for newer (older) cohorts.

Relatedly, four anomalies emerge in the REM literature. The first is a well-documented but largely ignored anomaly. REM studies are more likely to find evidence of soft expense manipulation than of production volume.[6] This is largely because of the differences in the matching of COGS and SG&A with current revenues and the different explanatory powers of the *ProductionCost* and *SoftExpense* models. The second anomaly is that older cohorts give the appearance of cutting soft expenses year after year, despite having little latitude in doing so. In contrast, newer cohorts appear to overinvest in intangibles. The third anomaly is that, unlike discretionary accruals that mean-revert to zero, firm-specific REM measures persist and do not revert over time (Siriviriyakul 2013; Cohen et al. 2014). Persistence of innate characteristics that get classified as so-called abnormal components explain this anomaly.

The fourth anomaly arises because a condition necessary for obtaining unbiased results from an empirical study is systematically violated in the *SoftExpense* model. [The error in estimated earnings management should be uncorrelated with the researcher's partitioning variable (McNichols and Wilson 1988).] In multi-cohort industry samples, abnormal soft expense is measured with an error—inclusive of innate intangible intensity—which in turn is strongly associated with the commonly studied financial and accounting characteristics. This causes spurious correlations between measured REM and financial characteristics (an omitted correlated

[6] See Cohen et al. (2008, p. 774), Gunny (2010, p. 870), McInnins and Collins (2011, p. 231), Zang (2012, p. 688), Siriviriyakul (2013, p. 46), Kim and Park (2014, p. 388), and Chan et al. (2015, p. 157).

variable problem). For example, newer cohorts not only show higher financial distress and growth but also appear to make excessive soft investments (Cohen et al. 2015). In contrast, older cohorts display financial stability but curtailed soft expenses. Hence, correlational tests suggest that financially healthy firms manipulate soft expenses.

Arguably, the aforesaid four anomalies could be addressed in a well-specified multivariate test that controls for innate intangible intensity. However, REM studies typically draw initial conclusions from, and conduct univariate tests on, residuals from the first-stage *SoftExpense* model. In addition, a measurement error in initial estimates can cause multi-collinearity problem in subsequent tests. For these reasons, Kothari et al. (2005) suggest controlling for innate characteristics in the first-stage models and apply this idea to discretionary accrual models. They also advocate a control group approach that does not impose any functional form on the relation between measured and control variables.

I examine potential improvements in the *SoftExpense* model because it is more often affected by innate characteristics than is the *ProductionCost* model. An ideal first-stage *SoftExpense* model would include an exogenous instrument that is highly correlated with innate intangible intensity but is unrelated to manipulated variables. The commonly used measures of intangible intensity—R&D expenditure and SG&A intensity—are manipulated variables in the REM context. Hence, I assess market-to-book ratio, proposed by Gunny (2010), and listing vintage, both of which are monotonic in intangible intensity. The listing vintage variable is not aimed at controlling for firm age, but to control for the vintage of the technological progress prevalent at the time of cohort's formation because it becomes a part of the cohort's persistent, innate characteristic. In addition, I examine the relative merits of using a regression approach versus using a control group matched on industry and intangible intensity.

I find that a control group matched on industry and listing age (that is, by comparing a firm against its listing cohort in the same industry) significantly ameliorates the anomalies identified in this study. If a regression approach is used then controlling for the fixed effects of listing age is not enough. An additional interaction term is required to control for the differences in the associations of successive cohorts with the key independent variable. (In this case, the SG&A matching with revenues.) A key take away from this finding is that both fixed and interaction effects of listing age should be included in the estimation of industry-based regressions. Controlling for market-to-book ratio does not satisfactorily address the cohort-related anomalies.

This paper makes two contributions to the literature. First, I document an intra-industry listing-cohort phenomenon, that successive listing cohorts within each industry have persistently higher innate intangible intensity. This is a new explanation for the well-documented increase in the listed firms' average intangible intensity over time, which is different from the explanation of changing industry composition offered by the prior studies. I extend the literature that examines the degree of IIH achieved with different industry classifications (Kahle and Walkling 1996; Fama and French 1997; Bhojraj et al. 2003; Hrazdil et al. 2013; Hoberg and Phillips 2015). I conclude that an additional layer of listing cohorts must be applied in each industry classification to achieve more homogeneous samples of firms. The study's recommendation that firms must be compared against their own cohorts in a given industry should interest a wide set of accounting, finance, management, and economics researchers who use industry-benchmarking models.

Second, I improve the literature's understanding of the REM models and contribute to its progress. I show that results from the REM models are influenced by the within-industry variations in innate intangible intensity as well as in the matching of SG&A with current revenues. Stated differently, results from this model are affected by dissimilarity of peer group. This pattern explains four anomalies in the REM literature. I suggest controlling for fixed and interaction effects of listing age in industry-based regressions or forming control groups matched on listing age and industry. Thus, this paper seeks to improve REM models similar to progress in abnormal accruals models (DeFond and Jiambalvo 1994; Dechow et al. 1995; Hribar and Collins 2002).

My paper is related to Siriviriyakul (2013) and Cohen et al. (2015). I extend those studies by providing economic reasons for the anomalies they identify. Cohen et al. (2015) recommend controlling for earnings performance in the first-stage model, which, they acknowledge (p. 6), may "throw the baby out with the bath water" in the detection of earnings manipulation. I suggest controlling for the fixed and interaction effects of listing age, which, given its exogenous nature, does not suffer from the same limitation. Listing age controls for not just the innate intangible intensity but also for a variety of factors such as growth, size, financial distress, and profitability that systematically differ with successive cohorts.

The rest of the paper proceeds as follows. Section 2 summarizes the literature and presents the hypotheses. Section 3 describes the sample selection and the measurement of the variables, and Section 4 examines univariate trends across listing cohorts. Section 5 describes the tests of the hypotheses. Section 6 describes some enhancements in existing models for future research. Section 7 presents concluding remarks.

## 2. Prior research, theory, and motivation of hypotheses

In this section I summarize prior literature and motivate hypotheses.

### *2.1. Intra-industry homogeneity assumption*

Many studies identify a firm's temporary, abnormal behavior by using the median industry characteristic as representative of the firm's unobserved behavior. These studies rely on an assumption of commonality in the products, services, and production, as well as delivery systems among the member firms of an industry (Guibert et al. 1971). For example, accounting studies that estimate discretionary accruals (Jones 1991), abnormal executive compensation (Core et al. 1999), real earnings management (Roychowdhury 2006), and errors in accruals (Dechow and Dichev 2002). However, recent literature questions the IIH assumption, and show that its violation leads to biased estimates of discretionary accruals (Hribar and Nichols 2007; Dopuch et al. 2012; Owens et al. 2014; Collins et al. 2014). Models for estimating discretionary accruals have evolved based on the progress of IIH literature (DeFond and Jiambalvo 1994; Dechow et al. 1995; Hribar and Collins 2002; Kothari et al. 2005). However, the implications of IIH violation are less-well understood in the context of REM models and cause anomalous results (Dechow et al. 2010; Siriviriyakul 2013; Cohen et al. 2015). I contribute to REM literature by demonstrating that the IIH assumption is systematically violated when firms from different listing cohorts are included in an industry-based study. In that case, an REM model could misinterpret the uniqueness of a firm's innate characteristic as its manipulative behavior and draw erroneous inferences.

### *2.2. Changes in the nature of a typical listed firm over time*

The nature of a typical listed firm has changed over time because physical assets command smaller rents than they did before the 1970s (Zingales 2000). As a result, U.S. firms tend to compete using intangible inputs such as R&D, specialized knowledge, and strategy, instead of tangible inputs such as inventory, material, energy, and labor (Shapiro and Varian 1998; Apte et al. 2008; Romer 1998; Baumol and Schramm 2010). Consistent with this fact, Srivastava (2014) documents increases in average R&D outlays, SG&A expenditures, and market-to-book ratios of the set of listed firms over time, indicative of increases in average intangible intensity.

*2.3. Changing characteristics of successive cohorts within industries*

Ritter and Welch (2002) and Srivastava (2014) find that newly listed firms are more likely to enter knowledge-intensive industries such as business services, communications, pharmaceuticals, healthcare, and computers. As a result, the industry composition of the listed firm population shifts over time from material-intensive industries towards knowledge-intensive industries. Hence Srivastava (2014) attributes the population-wide trend of increasing intangible intensity to the shifting industry composition of listed firms. However, he does not examine the trends or variations in the characteristics of firms within industries.

Prior literature supports the idea that successive cohorts within an industry show increasing intangible intensity. D'Aveni (1994) and Thomas and D'Aveni (2009) find that the competitive rivalries within industries have increased. Christensen (1997) argues that new firms in an industry are more likely to capitalize on technological innovations than do established firms. Other studies argue that newer companies more frequently innovate than legacy firms because they do not fear cannibalization of their existing products (Acs and Audretsch 1988; Igami 2015). Prahalad and Hamel (1990) and Brickley and Zimmerman (2010) claim that new firms obtain market shares from old firms by differentiating their products. A principal differentiation strategy over the last 40 years has been to offer advanced products and value-added services (Shapiro and Varian 1998; Baumol and Schramm 2010) and one-to-one relationship with customer (Payne and Frow 2005; Kumar and Reinartz 2012).[7] Innovation in products and provision of services requires more intangible inputs than the manufacture of commodity goods (Zingales 2000; Apte et al. 2008). Thus, new cohorts within an industry are likely to show higher intangible intensity than the previous cohorts. In addition, previous cohorts might not change their operating strategies at the

[7] For example, Amazon.com attracted book customers from Barnes & Noble by offering an online shopping experience. Tesla attracts automobile customers by offering a new product—an all-electric vehicle.

same pace as the new firms entering the same industry. In particular, firms tend to persist with business models they adopted in their formative years because any subsequent changes impose significant disruption costs (Hambrick 1983; Christensen 1997; Yip 2004; Chen et al. 2010). Studies examining "organizational imprinting" hypothesis support this idea (Stinchcombe 1965; Johnson 2007). This discussion implies that successive cohorts in a given industry are likely to use progressively higher intangible inputs in their business practice, leading to H1.

*H1: Newer cohorts show higher intangible intensity than older cohorts in the same industry and year.*

*2.4. Real earnings management*

Healy and Wahlen (1999, p. 368) state: "Earnings management occurs when managers use judgment in financial reporting and in structuring transactions to alter financial reports to either mislead some stakeholders about the underlying economic performance of the company or to influence contractual outcomes that depend on reported accounting numbers." Hence, managers could manipulate not only accounting but also operating and financing activities to alter financial reports. Prior studies find evidence consistent with this proposition.[8]

In a survey of financial executives, Graham et al. (2005) find that over 80% of chief financial officers are willing to cut soft expenses such as R&D and advertising to show higher earnings in the short term. Roychowdhury (2006) proposes an innovative method to detect this behavior. He reasons that the deviations in production costs and soft expenses from otherwise optimal operational decisions represent managers' attempt to bias earnings upward. He uses

[8] Managers liquidate inventory (Dhaliwal et al. 1994), sell long-term assets (Bartov 1993; Herrmann et al. 2003); reduce discretionary expenses (Bushee 1998; Baber et al. 1991) and R&D (Cohen et al. 2010); reduce sales prices (Jackson and Wilcox 2000); structure financial transactions (Barton 2001; Pincus and Rajgopal 2002; Dechow and Shakespeare 2009), leases (Imhoff and Thomas 1988), and debt-equity swaps (Hand 1989); and indulge in mergers and acquisitions (Ayers et al. 2002) and stock repurchases (Hribar et al. 2006) to manage earnings.

industry benchmarking to identify unobserved optimal outlays. He reasons that a firm's higher production costs (measured by COGS adjusted for inventory changes) and lower soft expenses (measured by SG&A expenses adjusted for R&D and advertising expenses) compared with peer industry firms (identified by two-digit SIC code) in a given year represent overproduction of goods and curtailment of discretionary soft expenses, respectively.

Roychowdhury (2006) further assumes that member firms from a given industry require similar levels of soft expenses and production costs to achieve a dollar of revenues. I call it the common-cost assumption. Based on this assumption, Roychowdhury (2006) measures a firm's deviations from its optimal outlays by the residuals from the regressions of COGS and SG&A on current revenues estimated by industry and year (*ProductionCost* and *SoftExpense* models, respectively). Roychowdhury (2006) shows that regression residuals are associated with the frequency of meeting earnings benchmarks and could represent earnings management. Many studies rely on these models to test their hypotheses.[9]

*2.5. Different explanatory powers of ProductionCost and SoftExpense models*

The Roychowdhury (2006) findings also indicate that the *ProductionCost* and *SoftExpense* models violate the common-cost assumption differently. COGS represents the direct manufacturing costs and the expensed portion of capitalized costs, both of which are typically traced to revenues. However, SG&A also includes investment outlays that are made in expectation of future revenues but are immediately expensed (Banker et al. 2011; Eisfeldt and Papanikolaou 2013). Hence, the correlation of SG&A with current revenues (0.39) is significantly lower than for

[9] Cohen et al. (2008) examine REM before and after the implementation of Sarbanes–Oxley Act; Cohen and Zarowin (2010) examine REM by seasoned equity offering firms; Gunny (2010) examines future performance of REM firms; Badertscher (2011) examines REM by overvalued firms; Zang (2012) examines tradeoffs between the real and the accruals-based earnings management; McInnis and Collins (2011) examine the association between REM and meet-or-beat of cash flow forecasts; Alissa et al. (2013) examines REM by firms aiming to improve their credit rating; Kim and Park (2014) examine the association between REM and client-retention decisions by auditors; and Chan et al. (2015) examine the effects of adopting compensation clawback provisions.

COGS (0.95) (Roychowdhury 2006, p. 350). As a result, the slope coefficient of the *SoftExpense* model (0.16) is significantly lower than that for the *ProductionCost* model (0.79) and the adjusted *R*-squares of the *ProductionCost* and *SoftExpense* models dramatically differ at 89% and 38%, respectively (Roychowdhury 2006, p. 349). Therefore, a majority of cross-sectional variation in SG&A is unrelated to variation in current revenues, and appears in regression residuals. Consequently, even though SG&A is smaller than COGS on average (Roychowdhury 2006, p. 347), the absolute values of the mean-zero residuals from the *SoftExpense* model could be larger than from the *ProductionCost* model. H2 derives from this discussion.

*H2: The magnitude and variance of residuals from a SoftExpense model are larger than from a ProductionCost model.*

Residuals from the *SoftExpense* model are inverse measures of manipulation of soft expense, while residuals from the *ProductionCost* model are direct measures of overproduction. H2 examines a potential reason for why researchers more frequently detect the former than the latter.

*2.6. Decreasing real earnings management over successive cohorts within industries*

Subsections 2.3 and 2.5 suggest that SG&A expenses of successive cohorts within a given industry include progressively higher amounts of one-off investments do not produce immediate benefits but that are expensed as incurred. Thus, successive listing cohorts within an industry might show little changes in COGS matching but display decreasing SG&A matching. Therefore, the misspecification of the *SoftExpense* model would increase and the explanatory power of the *SoftExpense* model would decline as newer cohorts are included in an industry sample. A large percentage of cross-sectional variation in dependent variable would appear in regression residuals rather be explained by the model. As a result, the newer (older) cohorts in each industry with their largest (smallest) innate SG&A intensity would show the most positive (negative) regression residuals.

*H3: Successive cohorts within each industry show progressively higher (or more positive) residuals from the SoftExpense model but do not show progressively lower (or more negative) residuals from the ProductionCost model to the same extent.*

H3 implies that oldest cohorts would appear to curtail their soft expenses but would appear not to manipulate their production volume to the same degree.

*2.7. Measures of financial distress for successive cohorts*

Intangible inputs often have a high fixed and low variable cost nature and can produce large growth if successful (Kaplan et al. 1990; Baumol and Swanson 2003). However, future benefits of intangible inputs are more uncertain than those of tangible inputs, on average (Holmstrom 1989; Kothari et al. 2002). Thus, intangible-intensive firms differ from other firms in their economic characteristics. Brown and Kapadia (2007) and Fama and French (2004) find that on average, successive cohorts grow faster but are more risky and less profitable. They examine the listed firm population as a whole. I extend these studies by reasoning that successive cohorts within each industry exhibit increasing likelihood of bankruptcy [Altman (1968) and Shumway (20010) measures], financial distress (loss in any of the preceding two years), and the need for external funds (significant debt or secondary equity raised).

*H4A: Successive cohorts within industries exhibit increasing financial distress.*

Older cohorts are likely to display soft-expense curtailment and low financial distress. As a result, the acts of soft-expense curtailment would appear to be negatively related with financial distress in cross-sectional tests. For the reasons that motivate H3, such patterns would be less apparent in the manipulation of production schedules.

*H4B: Measures of financial distress are negatively correlated with soft expense curtailment. This correlation is less significant for production schedule manipulation.*

## 3. Sample selection and measurement of variables

I use 53,996 firm-year observations with valid data in the Compustat database from 2001 to 2010.[10] I exclude all finance firms, because the traditional cost classifications (COGS versus SG&A accounts) do not apply to those firms. I exclude utility firms given the regulated cost structure in that industry (Givoly and Hayn 2000). The firms are classified consistent with Srivastava (2014) and Fama and French (2004). The listing year is the first year in which a firm has valid data in Compustat.[11] Firms listed before 1970 are classified as pre-1970 and as new firms otherwise. Each cohort of new firms is tied to a common listing decade and all firms are divided into five parsimonious groups for presentation purposes: Pre-1970 firms and cohorts for the 1970s, 1980s, 1990s, and 2000s. Monotonic trends in intangible intensity are observable in any manner of listing-year based classification. For example, classification based on listing year yields 40 groups that lead to even higher *t*-statistics. The distribution of firm-year observations by cohorts and years is presented in Table 1.

[Insert Table 1 near here]

### *3.1. Cost patterns and intangible intensity.*

Total expenses are calculated by subtracting income before extraordinary items (Compustat IB) from revenues (Compustat SALES) following Dichev and Tang (2008). SG&A and COGS intensities are calculated by dividing COGS (Compustat COGS) and SG&A

[10] Fifteen firm-year observations are required to estimate industry-year regressions consistent with Roychowdhury (2006). In addition, the sample requires data for estimating performance-matched discretionary accruals.

[11] Compustat listing year leads the listing year obtained from the Center for Research in Security Prices (CRSP) database by a few years. I use Compustat listing year to maintain consistency with financial data. Using CRSP listing year which merely shifts the cohort classification by a few years, does not affect the overall trends (results not tabulated).

(Compustat XSGA), respectively, by total expenses (Srivastava 2014). I measure intangible intensity by SG&A intensity, R&D expenditures, and market-to-book ratio. The detailed calculations are in the Appendix.

*3.2. Measurement of earnings management*

Consistent with prior literature, I use two measures of real activities manipulation and one measure of accounting manipulation.

*3.2.1. Overproduction*

Following Roychowdhury (2006), I estimate the following cross-sectional regression for each industry (two-digit SIC code) and year:

$$ProductionCost_{i,t}=\beta_1+\beta_2\times\frac{Sales_{i,t}}{Total\ Assets_{i,t\text{-}1}}+\beta_3\times\frac{\Delta Sales_{i,t}}{Total\ Assets_{i,t\text{-}1}}+\beta_4\times\frac{\Delta Sales_{i,t\text{-}1}}{Total\ Assets_{i,t\text{-}2}}+\epsilon_{i,t}\ , \qquad (1)$$

where *ProductionCost* is measured by COGS (Compustat COGS) plus changes in inventory (Compustat INVT) scaled by beginning-of-year assets (Compustat AT). *Sales* is measured by Compustat SALES and Δ*Sales* represents changes in revenues. The residual estimated on a firm-year basis represents a manipulation of production schedule. The higher the residual, the higher the manipulation, assuming that firms increase their production levels to spread the fixed costs over a larger number of units produced to show higher profit margins.

*3.2.2. Curtailment of soft expenses*

The following cross-sectional model is estimated for each industry (two-digit SIC code) and year:

$$SoftExpense_{i,t}=\beta_1+\beta_2\times\frac{1}{Total\ Assets_{i,t\text{-}1}}+\beta_3\times\frac{Sales_{i,t\text{-}1}}{Total\ Assets_{i,t\text{-}1}}+\epsilon_{i,t}, \qquad (2)$$

where *SoftExpense* is measured by SG&A (Compustat XSGA) plus advertising (Compustat XAD) and R&D expense (Compustat XRD) scaled by beginning-of-year assets, consistent with Roychowdhury (2006, p. 365). The residuals estimated on a firm-year basis are inverse measures of manipulation of soft expenses. The smaller (or more negative) the residuals, the higher the soft-expense curtailment.

*3.2.3. Measure of accounting manipulation*

I estimate the following cross-sectional model for each industry (two-digit SIC code) and year consistent with Kothari et al. (2005):

$$TotalCurrentAccruals_{i,t}=\beta_1 \times \frac{1}{Total\ Assets_{i,t\text{-}1}} + \beta_2 \times \frac{\Delta Sales_{i,t}\text{-}\Delta AR_{i,t}}{Total\ Assets_{i,t\text{-}1}} + \beta_3 \times \frac{PPE_{i,t}}{Total\ Assets_{i,t\text{-}1}} + \beta_4 \times ROA_{i,t} + \epsilon_{i,t}, \quad (3)$$

where *TotalCurrentAccruals* is measured using the balance sheet approach (see Appendix for details) and scaled by beginning-of-year assets. *AR* represents accounts receivable (Compustat RECT) and *PPE* represents property, plant, and equipment (Compustat PPEGT). Firm performance is controlled by return on assets (*ROA*). The residuals estimated on a firm-year basis are called performance-matched abnormal accruals and represent accounting manipulation.

*3.3. Financial characteristics and measures of financial distress*

I measure profitability by earnings-to-price ratio [Earnings per share (Compustat EPSFX) / Share price (Compustat PRCC_F)]. *SalesGrowth* is measure by the ratio of Δ*Sales* to *Sales*. I measure innate performance by operating cash flows deflated by beginning-of-year assets (Healy et al. 1992; Sloan 1996; Givoly and Hayn 2000; Dichev and Tang 2008).[12] I use Altman's Z-score (Altman 1968) and Shumway's measure (Shumway 2001) to estimate the likelihood of bankruptcy. A prior-loss firm reports negative net income (Compustat NI) in any of the prior two years. A firm is classified as in need of external funds if the sum of debt (Compustat DLTIS) and secondary equity issued (Compustat SSTK) exceeds 20% of total assets (Efendi et al. 2007). The detailed calculations are in the Appendix.

[12] This variable could also represent manipulation of operations (Roychowdhury 2006). In that case, my findings suggest that successive cohorts differ in both innate characteristics and REM.

## 4. Tests of hypotheses

Before testing the hypotheses, I examine the cross-sectional differences in the cost patterns of different industries.

*4.1. Cross-sectional differences in industries*

I classify firms into ten Fama and French (1997) industries after excluding finance and utility firms. Table 2 shows the number of firm-year observations and the pooled average characteristic by industry. Healthcare and business equipment industries have the highest *SoftExpense* indicating that they use a greater proportion of intangible inputs in their production functions than other industries. Retail and consumer durable industries have the highest *ProductionCost*, likely because of their inventory-intensive nature.

[Insert Table 2 near here]

COGS and SG&A intensities (Srivastava 2014) are measured differently from *ProductionCost* and *SoftExpense* (Roychowdhury 2006), respectively.[13] But Table 2 shows that COGS intensity is highly correlated with *ProductionCost* (correlation of 0.79, significant at *p*-value <0.01) and SG&A intensity is highly correlated with *SoftExpense* (correlation of 0.92, significant at *p*-value <0.01).

*4.2. Testing H1: Intra-industry trends in composition of costs*

I examine trends in the average cohort characteristics of each of the ten Fama and French (1997) industries. I obtain similar results by using two-digit SIC codes (results not tabulated). I estimate *ProductionCost* and *SoftExpense* on a firm-year basis from 2001 to 2010. I divide firms in each industry into five listing cohorts obtaining 50 industry-cohort observations. I estimate the average characteristics for each of the 50 industry-cohorts by pooling its observations. Panel A of

[13] *ProductionCost* includes an additional term of inventory change and *SoftExpense* includes R&D and advertising expenses. Moreover, *ProductionCost* and *SoftExpense* are deflated by total assets instead of total expenses.

Table 3 presents the average characteristics of each industry-cohort. It shows that large and systematic differences exist between *SoftExpense* of new and old cohorts in each industry. Also, the oldest and the newest cohorts lie at the opposite ends of the spectrum. *SoftExpense* for the 2000s cohort is at least two times higher than for pre-1970s firms in all industries, and is more than three times higher in seven out of ten industries. The table also shows the changing economic importance of soft versus production expenses across cohorts. While *ProductionCost* exceeds *SoftExpense* in all industries in all earlier cohorts, the trend reverses in seven out of ten industries in the latest cohort.

[Insert Table 3 near here]

I assign a *CohortDummy* of 0, 1, 2, 3, and 4, respectively, to Pre-1970 firms and 1970s, 1980s, 1990s, and 2000s cohorts. I calculate the cohort trend ($\beta_2$) in each industry by using its five cohort observations:

$$AverageCharacteristic_{Ind,Cohort} = \beta_{1,\mathrm{Ind}} + \beta_{2,\mathrm{Ind}} \times CohortDummy + \varepsilon. \quad (4)$$

A positive (negative) value of $\beta_2$ indicates increasing (decreasing) cohort trend in that industry. Panel A of Table 3 shows that the cohort trend in *SoftExpense* is positive and significant in nine out of ten industries. One industry for which the trend is not significant, *SoftExpense* for the 2000s cohort is still five times higher than for the pre-1970s cohort. The results for *ProductionCost* are less convincing though. Only two industries show statistically significant (negative) trends. I find similar results using R&D and market-to-book ratio as additional measures of intangible intensity. R&D is at least two times higher for the 2000s cohort than for pre-1970s firms in nine out of ten industries. I conduct all subsequent tests using SG&A as a measure of soft expense. All of the findings of this study holds if R&D is used as a measure of soft expense (results not tabulated).

Consistent with H1, these results indicate that newer cohorts use a higher proportion of intangible inputs in their business practice than do legacy firms from the same industry. Three explanations can account for these results. First, newer cohorts compete against older cohorts by offering innovative products and services than by manufacturing commodity products more cheaply; thus, they have innately higher intangible intensity (Christensen 1997; Shapiro and Varian 1998; Payne and Frow 2005; Baumol and Schramm 2010; Kumar and Reinartz 2012). Second, older cohorts curtail their soft expenses to a greater extent than newer cohorts. I distinguish between the first and second explanations by examining the explained component of the *SoftExpense* model in H2 tests that represents the non-manipulated outlays. The third explanation is that firms from different cohorts are in different stages of their life cycles and that firms in the early stages of their life cycle use more on intangible inputs than do mature firms (Jovanovic and MacDonald 1994).

*4.2.1. Controlling for life-cycle and survivorship bias explanations*

I control for the third (life-cycle) explanation by using a wider set of data from years 1970–2013. If different cohorts within each industry are similar in each respect except their listing years, contrary to the thesis of this study, then they should also be at the same stages of their life cycles at the same age. In that case, they should display similar intangible intensities when measured at the same number of years after their listing years. For example, two pharmaceutical companies that went public in 1970 and 1990 should look similar when observed in 1980 and 2000, respectively. I test this proposition by observing all firms' intangible intensities at two intervals of five and ten years after their listing years. Then I calculate the revised cohort trends for each industry using equation (4).

Panel B of Table 3 presents these revised cohort trends. I continue to find positive and significant cohort trends similar to those discussed in Subsection 4.2. Results suggest that differences across successive cohorts in an industry are persistent and that cannot be explained by life-cycle hypothesis. In addition, Panel C of Table 3 shows increases in the average intangible intensity of each industry over time.[14] This result demonstrates that the arrival of each new cohort permanently shifts the average intangible intensity of an industry to a higher notch. These results are consistent with the idea that successive cohorts in each industry adopt more intangible-intensive business model in their formative years, based on extant progress in technology, but persist with it irrespective of future technological developments (Hambrick 1983; Christensen 1997; Yip 2004). These results also show that life-cycle effect and survivorship bias cannot fully explain the inter-cohort trends, supporting my claim that the intra-industry listing-cohort is an unexamined new phenomenon.

*4.2.2. Similarity of firms in same cohorts versus similarity of firms in same industry*

I calculate averages of intangible intensity for 50 industry-cohorts (ten industries × five cohorts) using data from 2001 to 2010. I then estimate variance of intangible intensity across ten industries in each of the five cohorts. I also calculate variance across five cohorts in each of the ten industries. Panel D of Table 3 shows that the average standard deviation of *SoftExpense* across industries for a given cohort (0.188) is smaller than the average standard deviation across cohorts for a given industry (0.244). This suggests that the characteristics across industries in a given cohort are more similar than the characteristics across cohorts in a given industry. A corollary of this finding is that more homogeneous samples are obtainable by parsing firms with listing cohorts than with industries. Hence, my study extends the literature that examines the degree of IIH

[14] However, these results could be affected by other factors such as changes in accounting rules and Compustat's definition of variables, which do not affect my main results using data from same years.

achieved by different industry classifications (Kahle and Walkling 1996; Fama and French 1997; Bhojraj et al. 2003; Hrazdil et al. 2013). I conclude that an additional layer of listing cohorts must be applied in each industry classification to achieve more homogeneous samples.

*4.3. Testing H2*

The greater the variation in mean-zero regressions residuals from equations (1) and (2) in a sample of firms, the larger the likelihood of detecting significant manipulation of operations. I test H2 by examining whether the variation in residuals from equation (2) exceed the variation in residuals from equation (1). I test this idea by using each of the Fama and French industry as a unit of observation.

I first estimate the discretionary components of *SoftExpense* and *ProductionCost* on a firm-year basis using equation (1) and equation (2), respectively, which should average zero for each two-digit SIC code. I then estimate the pooled averages of their absolute values by Fama-French classification, a broader classification than the two-digit SIC code. This measure is similar to mean absolute deviation. I call it within-industry variation and obtain ten observations for it. I test H2 by examining whether the mean, the range, and the standard deviation of the ten within-industry variations of soft-expense manipulation exceed similar statistics for production-schedule manipulation.

Table 4 shows results consistent with H2. The variations of soft-expense manipulation exceed variations of production-schedule manipulation for all industries. The mean of the former is twice that of the latter (0.335 versus 0.156) and the standard deviation of the former is five times higher than the latter (0.122 versus 0.026). Both differences are statistically significantly (*p*-value <0.01). In addition, the range of the former is four times larger than the latter (0.344 versus 0.079).

These patterns are opposite of what is presented in Table 2, which shows that the raw values of *ProductionCost* exceed *SoftExpense*s in most industries.

[Insert Table 4 near here]

These results provide a potential reason why a researcher is more likely to detect a manipulation of soft expenses than of production volumes. I contribute to the literature by highlighting this largely-ignored anomaly, which I conclude, arises from a fundamental difference in the accounting of costs recognized in the COGS and SG&A categories. COGS' recognition is typically traced to revenues. But SG&A includes investment outlays that are expensed as incurred. This differential success in matching the two types of core expenses to current revenues (Dichev and Tang 2008) leads to significantly larger SG&A residuals than COGS residuals and could be misinterpreted as a greater evidence of manipulation of soft expense than of production volume.[15]

Table 4 shows a strong correlation of 0.95 (*p*-value <0.01) between the absolute value of the discretionary component of *SoftExpense* and its nondiscretionary component. This correlation implies that intangible-intensive industries display greater cross-sectional variation of *SoftExpense*s among their member firms. Thus the higher the innate intangible intensity in a group of firms, the greater the likelihood of detecting manipulated *SoftExpense* for at least some firms in that group. This idea does not equally apply to *ProductionCost* because the correlation between the absolute value of the discretionary component and its nondiscretionary component is insignificant (0.197, *p*-value of 0.58).

[15] Cohen et al. (2008, Fig. 4, p. 774) find that the magnitude of abnormal soft expense is three to five times higher than the magnitude of abnormal production cost. McInnis and Collins (2011, pp. 231, 232) find a significant difference in the manipulation of soft expense by treatment and control firms but no such difference in the manipulation of production volume. Kim and Park (2014, p. 388) find a significant (no significant) relation between auditor resignation of suspect clients and abnormal soft expense (abnormal production expense). Siriviriyakul (2013, p. 46) finds a significant (no significant) difference between abnormal soft expense (abnormal production expense) of small-loss and small-profit firms; Chan et al. (2015, p. 157) find a significant (no significant) relation between the adoption of clawback provisions and abnormal soft expenses (abnormal production expenses).

*4.4. Testing H3: Intra-industry cohort trends in innate costs and earnings management*

I calculate the discretionary and the nondiscretionary components of *ProductionCost*, *SoftExpense*, and *TotalCurrentAccruals* on a firm-year basis using equations (1), (2), and (3). I then estimate their pooled averages by 50 industry-cohorts. I estimate cohort trends for each of these variables for each industry by using five industry-cohort observations in equation (4).

Panel A of Table 5 shows increasing trends in the discretionary component of *SoftExpense* in most industries, similar to the trends of their initial values. The trends in eight out of ten industries are statistically significant. The results on the discretionary components of *ProductionCost* are less significant. Only two industries show significant declines in the discretionary component of *ProductionCost* across cohorts. These results imply that a researcher would observe significant and systematic curtailment (excessive investment) of soft outlays by older (newer) cohorts in each industry. But she would find less convincing evidence on the manipulation of production volumes. Both results are consistent with H3.

[Insert Table 5 near here]

*4.4.1. Intra-industry cohort trends in innate characteristics*

Panel A of Table 5 shows that the trends documented in Subsection 5.3 are not limited to the discretionary component of *SoftExpense* and also appear in its nondiscretionary component in a very similar manner. Six out of seven industries that exhibit significant positive trends in the nondiscretionary components also show positive cohorts trends in the discretionary component. Furthermore, most industries show a significant negative trend in cash flows and the nondiscretionary component of *TotalCurrentAccruals*, both of which represent innate characteristics (Panel B of Table 5).[16] Successive cohorts also exhibit increasing growth

[16] Variation in cash flows could reflect variations in innate characteristics (Givoly and Hayn 2000; Dichev and Tang 2008) or REM (Roychowdhury 2006).

(*SalesGrowth*) and decreasing profitability (earnings-to-price ratio). These patterns clearly show that successive cohorts within an industry differ systematically in their economic, financial, and accounting characteristics.

Results suggest that the inclusion of different cohorts in a cross-sectional sample, a common and increasing occurrence in industry-benchmarked empirical studies, violates the IIH assumption. This findings should interest a wide set of studies and not just REM studies. For example, Panel B of Table 5 shows that the magnitude of discretionary accruals increases across cohorts. The overtime increase in their magnitude (Dopuch et al. 2012; Owens et al. 2014) can be thus explained by the inclusion of newer cohorts in firm samples.

*4.4.2. Additional tests by using annual data*

Tests described in Subsections 4.4 and 4.4.1 are conducted by pooling firm-year observations over a common ten-year period of 2001–2010. I conduct an additional test by pooling data by year, which is more representative of a typical empirical test. I calculate the pooled averages of firm-year observations of the discretionary and nondiscretionary components of *SoftExpense*s by industry, year, and cohort [five hundred samples (ten years × ten industries × five cohorts)]. I then estimate equation (4) to estimate cohort trends separately for each industry and year by using its five cohort observations (one hundred regressions). The cohort trends for the discretionary and the nondiscretionary components of *SoftExpense*s for each of the 100 industry-years are presented in Panels C and D of Table 5, respectively. I examine whether the average of ten annual cohort trends in each industry is significantly different from zero (Fama and MacBeth 1973).[17] The last columns indicate that the average cohort trend is positive and significant in all industries. I also calculate the average of ten industry cohort trends in each year. This average is

[17] I obtain similar results using the Newey-West (1987) adjustment for standard errors (results not tabulated).

significantly positive in all years showing that both discretionary and nondiscretionary components exhibit positive cohort trends.

These results imply that irrespective of the industry or year examined, older cohorts have both smaller innate *SoftExpense* and more negative discretionary *SoftExpense* than newer cohorts. Thus, older cohorts appear to curtail *SoftExpense* year after year despite having the least latitude to do so. Based on H1, H2, and H3 tests, a more compelling explanation is that the distinctive innate characteristics of older cohorts could be misinterpreted as discretionary curtailment of soft outlays.

*4.4.3. Anomalies documented in prior literature*

H1–H3 results explain one anomaly in the REM literature—that the *SoftExpense* model more frequently finds results consistent with manipulated operations than does the *ProductionCost* model. H1–H3 results also explain two other anomalies in the REM literature. First, unlike discretionary accruals that mean-revert to zero over time, firm-specific REM measures persist and show non-reversal (Siriviriyakul 2013; Cohen et al. 2014). This phenomenon can be explained by the persistence in firms' innate production functions. Second, Cohen et al. (2015, p. 42) find that high sales growth, price-to-earnings ratio, and market-to-book ratio firms show large positive SG&A residuals. These patterns can be explained by the distinctive characteristics of younger cohorts.

*4.5. Testing H4A: Cohort trends in measures of financial distress*

I calculate the average measures of financial distress for each cohort using pooled firm-year data from the common years 2001–2010. I estimate equation (4) to obtain overall cohort trends. Panel A of Table 6 shows that successive cohorts have increasing likelihood of prior loss: 32.70%, 41.66%, 49.55%, and 57.48%; likelihood of bankruptcy (Altman): 15.84%, 18.07%, 23.82%, 32.51%, and 37.61%; likelihood of bankruptcy (Shumway): 0.02%, 0.10%, 0.26%, 0.43%, and 0.55%; and need for external funds: 12.21%, 15.80%, 18.49%, 21.12%, and 29.19%. All of these trends are statistically significant ($p$-value < 0.01). I obtain similar results by estimating cohort trends by industries as shown in Panel B of Table 6, consistent with H4A.

[Insert Table 6 near here]

*4.5.1. Testing H4B: Correlation between measures of financial distress and earnings management*

I calculate the average measures of earnings management and financial distress for each industry-cohort. This gives me 50 industry-cohort observations for each variable. I use these 50 observations to examine correlations between the two measures of REM and the four measures of financial distress.

Results presented in Panel A of Table 7 show that the discretionary component of *SoftExpense* is positively correlated with three out of four measures of financial distress. These results suggest that financially distressed firms, despite their higher capital market incentives, manipulate soft expenses to a lesser extent than financially healthy firms. This anomalous result runs contrary to a well-accepted proposition that earnings management increases with financial distress and capital market incentives (Dechow et al. 2010). Notably, the correlations between the discretionary component of *ProductionCost* and measures of financial distress are not significant.

[Insert Table 7 near here]

A more compelling explanation for H4B findings is that new and intangible-intensive firms are characterized by both high financial distress and high innate *SoftExpense*. Thus, in cross-sectional tests, the common characteristics appear to be positively correlated, likely reflecting the omitted correlated variable of intangible intensity. This idea is supported by Panel B which shows similar results as Panel A despite using the nonmanipulated component of *SoftExpense*.[18]

### *4.5.2. Spurious correlations*

The H4B results illustrate how a less careful application of the *SoftExpense* model could lead to erroneous inferences. A spurious correlation would be detected to the extent that a firm's distinctive ways of doing business is related to both a variable of interest (e.g., profitability, capital structure, or financial reporting quality) and production function (e.g., SG&A intensity or R&D expenditures). In that case, soft expense manipulation would appear to be associated with the financial characteristic of interest.

## 5. Controlling for innate intangible intensity in calculation of abnormal *SoftExpense*

Results so far suggest that innate characteristic is reflected in the estimates of abnormal or manipulated variables, which could cause spurious correlations in subsequent tests (McNichols and Wilson 1988). Kothari et al. (2005) suggests controlling for innate characteristics in the first-stage estimates of earnings management instead of leaving their correction to a subsequent multivariate test. This is because studies often draw initial conclusions from the patterns of, and the univariate tests on, first-stage estimates of earnings management. Also, second-stage multivariate tests could show biased coefficients because of multicollinearity.

Results so far indicate that firms with high (low) innate intangible intensity could be classified as having excessive (curtailed) *SoftExpense*. The association between the innate production function and the measured manipulation is of a lesser concern in the *ProductionCost* model. Thus, I focus on the *SoftExpense* model for potential improvements. I evaluate two

[18] Furthermore, the nonmanipulated component of *ProductionCosts* is strongly negatively correlated with measures of financial distress, consistent with the proposition that material-intensive firms have lower financial distress than intangible-intensive firms, on average.

methods. In the first method, I control for a variable that is highly correlated with innate intangible intensity but not with manipulated variable. In particular, I assess: 1) market-to-book ratio proposed by Gunny (2010) and 2) the firm's listing age, because the successive cohorts show monotonic patterns in both listing age and intangible intensity. I do not examine two commonly used measures of intangible intensity—R&D expenditures and SG&A intensity—because they are manipulated variables in the REM context. I estimate the regression

$$SoftExpense_{i,t}=\beta_1+\beta_2\times\frac{1}{Total\ Assets_{i,t\text{-}1}}+\beta_3\times\frac{Sales_{i,t\text{-}1}}{Total\ Assets_{i,t\text{-}1}}+\beta_4\times ControlInnateIntangibleIntensity_{i,t}$$
$$+\ \beta_5\times ControlInnateIntangibleIntensity_{i,t}\times\frac{Sales_{i,t\text{-}1}}{Total\ Assets_{i,t\text{-}1}}+\epsilon_{i,t}.,\qquad (5)$$

where *ControlInnateIntangibleIntensity* is either *MarketToBook* ratio or *ListVintage*. *MarketToBook* ratio is defined in Subsection 3.3. *ListVintage* is the difference between listing year and sample-formation year, expressed in years. In the sample-formation year, it represents the vintage of the technology prevalent at the time of the cohort formation. The interaction term between *Sales* and *ControlInnateIntangibleIntensity* controls for the variation in matching between SG&A and revenues arising from inter-cohort differences in intangible intensity. Because REM models require a minimum of 15 firm-year observations to estimate each regression (Roychowdhury 2006), the addition of two terms should leave enough degrees of freedom to estimate equation (5). *ModifiedAbnormalSoftExpense* is the residual from the revised models.

In the second approach, I form two control groups of firms, one matched on *MarketToBook* ratio and the other matched on *ListVintage*. (Both also matched on industry.) *ModifiedAbnormalSoftExpense* is the difference of *SoftExpense* residuals of the sample and control firms (Kothari et al. 2005).

*5.1. Revised inter-cohort trends*

I obtain four estimates of *ModifiedAbnormalSoftExpense* for each firm year by using one of the above four approaches [(*ListVintage / MarketToBook*) × (first-stage control / matched-pair approach)] at a time. I estimate the overall cohort-trends and the industry-wise cohort trends using these modified measures and present them in Panels A and B of Table 8. The cohort trends become insignificant once I control for *ListVintage* in either manner. However, the control of *MarketToBook* appears less effective in addressing the listing cohort phenomenon.

[Insert Table 8 near here]

*5.2. Association between financial distress and revised measures of earnings management*

I repeat H4B tests described in Subsection 5.4.1 using one of the four measures *of ModifiedAbnormalSoftExpense* at a time. The results and presented in Panels A–D of Table 9. The correlations between the measures of financial distress and soft expenses manipulation become insignificant when *ModifiedAbnormalSoftExpense* is estimated after controlling for *ListVintage* with a regression or matched-pair approach. However, I continue to find significant correlations after controlling for *MarketToBook* ratio.

[Insert Table 9 near here]

These results indicate that *ListVintage* is an effective control for cohort-related anomalies identified in this study.

*5.4. General enhancement in all models that rely on the IIH assumption*

The corrections proposed in *ModifiedAbnormalSoftExpense* should be generalizable to all studies that use industry benchmarking and rely on IIH assumption. Listing age appears to be a parsimonious and effective instrumental variable to control for differences in characteristics of successive cohorts measured in a given year (inter-cohort differences, life-cycle effects, and survivorship biases). Furthermore, it is a truly exogenous variable. Other controls such as return on assets (ROA) and R&D might be endogenously related to manipulated variable. Thus, controlling for them might "throw the baby out with the bath water," thereby lowering the power of tests or making them "more difficult to reject a false null" (Cohen et al. 2015 p. 6). Thus, industry-benchmarking models must either use an additional layer of listing cohorts or somehow control for fixed and interaction effects of *ListVintage*. Notably, *ListVintage* is also strongly associated with characteristics such as size, growth, profitability, and financial distress that are commonly controlled in a multivariate test.

## 6. Conclusion

Many studies identify a firm's abnormal or opportunist act by industry benchmarking. These studies assume commonality in the production functions and its associated characteristics among the members firms of an industry. I show that this assumption is systematically violated when firms from different listing cohorts are included in an industry sample. This is because successive cohorts in a given industry differ monotonically in their production functions as well as in their economic, financial, and accounting characteristics that are typically associated with production function. In particular, successive cohorts show increasing market-to-book ratio, SG&A intensity, R&D expenditures, sales growth and bankruptcy risks, and decreasing profitability, cash flows, and accruals. Life-cycle effects and survivorship biases cannot fully account for these differences. My findings are consistent with the idea that newer cohorts in an industry compete against legacy firms by offering innovative products and services that require more intangible inputs than do cost-based competitive strategies. Also, the results are consistent with organizational imprinting hypothesis that firms in their formative years readily adopt latest technologies, but tend to persist with them despite subsequent technological progress.

Given the systematic intra-industry differences across successive listing cohorts, firms with innately different characteristic than industry median could be misclassified as engaged in abnormal or manipulative acts. This pattern most often affects the oldest and newest cohorts in each industry that lie at the opposite ends of the financial characteristic spectrum. Consistent with this idea, REM models characterize oldest cohorts as persistently cutting soft expenses. Also, youngest firms are portrayed as being the least manipulative despite their having the highest incentives to manipulate earnings.

The cohort-related anomalies are significantly ameliorated by using a control group matched on industry and listing age. If industry-based regression is estimated then both fixed and interaction terms of listing age are required to control for inter-cohort differences in the levels of the dependent variable and in its associations with key independent variables. I contribute to the studies in economics, finance, and accounting literature that use industry benchmarking. My results clearly show that classification of firms by industries is not enough. An additional layer of listing cohorts must be applied in all industry classifications to achieve more homogeneous samples.

I contribute to the accounting literature by improve the understanding of the REM models. I show that results from REM models are affected by the within-industry variations in innate intangible intensity and in the matching of SG&A with current revenues. I identify or explain four anomalies in the REM literature: a more frequent detection of soft-expense manipulation than of production volume, the appearance of old cohorts' perpetual curtailment of their soft expenses, the appearance of low REM by financially distressed firms, and the persistence and non-reversal of firm-specific REM. I suggest parsimonious enhancements in REM models for future research.

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**Appendix**
Definitions of variables

Variable names are in italics. 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 |
| *SG&A Intensity* | = | Selling, general, and administrative expenses (XSGA)/Total Expenses |
| *COGS Intensity* | = | Cost of goods gold (COGS)/Total Expenses |
| *R&D* | = | R&D expense (XRD)]/ Total Assets at the beginning of the year |
| *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)]/ Total Assets at the beginning of the year |
| *ProductionCost* | = | [COGS (COGS) + changes in inventory (INVT)]/ Total Assets at the beginning of the year |
| *SoftExpense* | = | [SG&A expenses (CXSGA) plus advertising (XAD) and R&D expense (XRD)]/ Total Assets at the beginning of the year |
| *AR* | = | Accounts receivable (Compustat RECT) |
| *PPE* | = | Property, plant, and equipment (PPEGT) |
| Return on assets (*ROA*) | = | Return on assets [Net income (NI) / Average Total Assets] |
| Components of *ProductionCost* | = | The following equation is estimated by industry (two-digit SIC code) and year consistent with (Roychowdhury 2006). $ProductionCost_{i,t}=\beta_1+\beta_2\times\frac{Sales_{i,t}}{Total\ Assets_{i,t-1}}+\beta_3\times\frac{\Delta Sales_{i,t}}{Total\ Assets_{i,t-1}}+\beta_4\times\frac{\Delta Sales_{i,t-1}}{Total\ Assets_{i,t-2}}+\epsilon_{i,t}$ Industry-years with fewer than firm-year 15 observations are excluded. The explained portion is called the nondiscretionary component. The regression residual is called the discretionary component or the *AbnormalProductionCost*. |
| Components of *SoftExpense* | = | The following equation is estimated by industry (two-digit SIC code) and year consistent with Roychowdhury (2006). $SoftExpense_{i,t}=\beta_1+\beta_2\times\frac{1}{Total\ Assets_{i,t-1}}+\beta_3\times\frac{Sales_{i,t-1}}{Total\ Assets_{i,t-1}}+\epsilon_{i,t}$ Industry-years with fewer than firm-year 15 observations are excluded. The explained portion is called the nondiscretionary component. The regression residual is called the discretionary component or *AbnormalSoftExpense*. |
| Components of *Accruals* | = | The following equation is estimated by industry (two-digit SIC code) and year consistent with Kothari et al. (2005) $TotalCurrentAccruals_{i,t}=\beta_1\times\frac{1}{Total\ Assets_{i,t-1}}+\beta_2\times\frac{\Delta Sales_{i,t}-\Delta AR_{i,t}}{Total\ Assets_{i,t-1}}+\beta_3\times\frac{PPE_{i,t}}{Total\ Assets_{i,t-1}}+\beta_4\times ROA_{i,t}+\epsilon_{i.t}$ The explained portion is called the nondiscretionary component. The regression residual is called the discretionary component. |

**Appendix continued**

| | | |
|---|---|---|
| *PriorLoss* | = | A dummy variable that takes the value of one if the firm reports negative net income (NI) in any of the prior two years; and zero, otherwise. |
| Cash flow from operations (*CFO*) | = | Cash flow from operating activities (OANCF)/ Total Assets at the beginning of the year |
| *Earning-To-Price* ratio (*E/P*) | = | Earnings per share (EPSFX) / Share price (PRCC_F) |
| *SalesGrowth* | = | [SALE – Lag(SALE)]/ Lag(SALE) |
| Need for external funds | = | A firm is classified as in need of external funds if the sum of debt (DLTIS) and secondary equity issued (SSTK) exceeds 20% of total assets (Efendi et al. 2007). |
| Altman's bankruptcy | = | I first calculate the Z-score using the formula 1.2 × [working capital (WCAP) / Total Assets] + 1.4 × [retained earnings (RE) / Total Assets] + 3.3 × [net income (NI) + interest expense (XINT) + tax expense (TXT)] / Total Assets + 0.6 × [Share price (PRCC_F) × number of Shares Outstanding (CSHO)] / total liabilities (LT) + 0.999 × (revenues / Total Assets). Firms with a Z-score of less than 1.8 are classified as high likelihood of bankruptcy firms. |
| Shumway's bankruptcy | = | If first calculate the following: Variable = −13.303 −1.982 × (net income / Total Assets) + (3.593 × total liabilities/ Total Assets) −0.467 × [Log of share price (PRCC_F) × number of shares outstanding (CSHO)] – 1.809 × abnormal return [difference between firms' annual stock return (CRSP RET) and market return (CRSP VWRETD)] + 5.791 × (standard deviation of 12 residuals from annual regression of monthly stock returns on market returns). Shumway's bankruptcy = $\frac{e^{Variable}}{(1 + e^{Variable})}$ |
| Listing year | = | The first year in which a firm's data are available in Compustat is the listing year. |
| Listing cohort | = | All firms with a listing year before 1970 are classified as Pre-1970 firms. The remaining firms are classified as new firms. All of the cohorts listed in a common decade constitute a cohort of new firms. Consequently, all of the firms are divided into Pre-1970 firms or a cohort from the 1970s, 1980s, 1990s, or 2000s. |
| *ListVintage* | = | The difference between listing year and current year, expressed in years |

**Appendix continued**

| Modified discretionary component of *SoftExpense* (*ModifiedAbnormalSoftExpense*) | |
|---|---|
| Control for *MarketToBook* ratio or *ListVintage* | The following equation is estimated by industry (two−digit SIC code) and year consistent with (Roychowdhury 2006). $SoftExpense_{i,t}=\beta_1+\beta_2\times\frac{1}{Total\ Assets_{i,t\text{-}1}}+\beta_3\times\frac{Sales_{i,t\text{-}1}}{Total\ Assets_{i,t\text{-}1}}+\beta_4\times ControlInnateIntangibleIntensity_{i,t}+\beta_5\times ControlInnateIntangibleIntensity_{i,t}\times\frac{Sales_{i,t\text{-}1}}{Total\ Assets_{i,t\text{-}1}}+\epsilon_{i,t}$, where *ControlInnateIntangibleIntensity* is either *MarketToBook* ratio or *ListVintage*. Industry-years with less than firm-year 15 observations are excluded. The regression residual is called the *ModifiedAbnormalSoftExpense*. |
| Matched-pair approach | I form two control groups of firms from the same industry, one matched on *MarketToBook* ratio and the other matched on *ListVintage*. (Both matched on industry.) *ModifiedAbnormalSoftExpense* is the difference of *AbnormalSoftExpense* of the sample and control firms (Kothari et al. 2005). |

All continuous variables are winsorized at the 1st and 99th percentiles.

**Table 1**
Number of observations per listing cohort

The first year in which a firm's data are available in Compustat is the listing year. All firms with listing year after 2009 are excluded (Srivastava 2014). The remaining firms are divided into five listing cohorts. All firms with a listing year before 1970 are classified as Pre-1970 firms. The remaining firms are classified as new firms. All of the cohorts listed in a common decade constitute a cohort of new firms. Consequently, all of the firms are divided into Pre-1970 firms or a cohort from the 1970s, 1980s, 1990s, or 2000s.

| Fiscal year | Total number of firms | Pre-1970 firms | 1970s cohort | 1980s cohort | 1990s cohort | 2000s cohort |
|---|---|---|---|---|---|---|
| 2001 | 5,987 | 501 | 465 | 976 | 2,742 | 1,303 |
| 2002 | 5,900 | 486 | 445 | 909 | 2,481 | 1,579 |
| 2003 | 5,733 | 479 | 414 | 853 | 2,253 | 1,734 |
| 2004 | 5,678 | 467 | 392 | 811 | 2,087 | 1,921 |
| 2005 | 5,521 | 439 | 358 | 753 | 1,912 | 2,059 |
| 2006 | 5,355 | 421 | 335 | 687 | 1,764 | 2,148 |
| 2007 | 5,203 | 391 | 307 | 623 | 1,583 | 2,299 |
| 2008 | 5,074 | 380 | 292 | 569 | 1,454 | 2,379 |
| 2009 | 4,962 | 370 | 289 | 539 | 1,340 | 2,424 |
| 2010 | 4,583 | 361 | 276 | 500 | 1,240 | 2,206 |
| Total | 53,996 | 4,295 | 3,573 | 7,220 | 18,856 | 20,052 |

**Table 2**

Cross-sectional analysis: Average cost attributes by Fama and French 12-industry classification

All of the firms are grouped by the Fama and French 12-industry classification. Industries representing finance firms (industry code 11) and utility firms (industry code 8) are excluded. The table presents the average attributes of each industry calculated by using all of the pooled firm-year observations from that industry from 2001 to 2010. These attributes are calculated by using the methods described in the Appendix. The top (bottom) two industries for each attribute are highlighted in bold (bold italic) letters.

| Industry | Fama and French industry code | Number of firm-year observations | *COGS Intensity* | *SG&A Intensity* | *ProductionCost* | *SoftExpense* |
|---|---|---|---|---|---|---|
| Consumer nondurables | 1 | 3,134 | 0.616 | 0.296 | 0.894 | 0.579 |
| Consumer durables | 2 | 1,677 | 0.661 | 0.264 | **0.970** | 0.674 |
| Manufacturing and printing | 3 | 6,624 | **0.690** | ***0.224*** | 0.869 | ***0.444*** |
| Oil, gas, and coal | 4 | 3,890 | 0.509 | ***0.227*** | ***0.445*** | ***0.377*** |
| Chemicals and allied products | 5 | 1,666 | 0.607 | 0.300 | 0.751 | 0.638 |
| Business equipment | 6 | 13,327 | 0.447 | **0.452** | 0.584 | **0.872** |
| Telephone and television | 7 | 2,256 | ***0.436*** | 0.299 | 0.474 | 0.541 |
| Wholesale, retail | 9 | 5,652 | **0.704** | 0.238 | **1.664** | 0.636 |
| Healthcare | 10 | 5,921 | ***0.386*** | **0.551** | ***0.477*** | **1.045** |
| Other | 12 | 9,849 | 0.582 | 0.378 | 0.661 | 0.697 |

Correlation between *COGS Intensity* and *ProductionCost* is 0.79 (*p*-value <0.01)

Correlation between *SG&A Intensity* and *SoftExpense* is 0.92 (*p*-value <0.01)

**Table 3**

Trends in cost characteristics of successive cohorts of listed firms by Fama and French 12-industry classification

The first year in which a firm's data are available in Compustat is the listing year. All firms with listing year after 2009 are excluded (Srivastava 2014). The remaining firms are divided into five listing cohorts. All firms with a listing year before 1970 are classified as Pre-1970 firms. The remaining firms are classified as new firms. All of the cohorts listed in a common decade constitute a cohort of new firms. Consequently, all of the firms are divided into Pre-1970 firms or a cohort from the 1970s, 1980s, 1990s, or 2000s. These five cohorts are assigned *CohortDummy* of 0, 1, 2, 3, and 4, respectively. All of the firms are sorted by the Fama and French 12-ndustry classification. Industries representing finance firms (industry code 11) and utility firms (industry code 8) are excluded. All variables are defined in the Appendix. The average characteristic of each cohort in each Fama and French industry is calculated using pooled data from 2001 to 2010 for Panels A and D and from 1970 to 2013 for Panel B and C. The cohort trend is calculated for each Fama and French industry using the following equation and five observations from five cohorts: $AverageCohortCharacteristic = \beta_1 + \beta_2 \times CohortDummy + \varepsilon$. $\beta_2$ represents the trend in average firm characteristics across successive cohorts in an industry. *, **, and *** indicates significance at the 10%, 5%, and 1% level, respectively on a one-tailed basis.

Panel A: Cost characteristics of successive cohorts of listed firms, measured at the same time

| Industry | Cohort | *Production Cost* | *Soft Expense* | *Market-To-Book ratio* | *R&D* |
|---|---|---|---|---|---|
| Consumer nondurables | Pre-1970 firms | 0.821 | 0.396 | 1.842 | 0.005 |
| | 1970s cohort | 1.066 | 0.401 | 1.266 | 0.006 |
| | 1980s cohort | 1.079 | 0.640 | 2.004 | 0.011 |
| | 1990s cohort | 0.857 | 0.451 | 1.649 | 0.009 |
| | 2000s cohort | 0.837 | 0.921 | 2.942 | 0.020 |
| | Cohort trend ($\beta_2$) | −0.018 | 0.110 | 0.258 | 0.003 |
| | *t*-statistic | *−0.388* | *2.133** | 1.501 | *2.972*** |
| Consumer durables | Pre-1970 firms | 0.950 | 0.252 | 1.363 | 0.019 |
| | 1970s cohort | 0.954 | 0.593 | 2.158 | 0.021 |
| | 1980s cohort | 1.040 | 0.649 | 2.229 | 0.058 |
| | 1990s cohort | 0.977 | 0.666 | 2.605 | 0.065 |
| | 2000s cohort | 0.932 | 1.018 | 3.190 | 0.078 |
| | Cohort trend ($\beta_2$) | −0.001 | 0.161 | 0.410 | 0.016 |
| | *t*-statistic | *−0.075* | *4.468**** | 6.883*** | *5.708**** |
| Manufacturing and printing | Pre-1970 firms | 0.821 | 0.206 | 1.423 | 0.016 |
| | 1970s cohort | 0.952 | 0.275 | 1.765 | 0.023 |
| | 1980s cohort | 0.931 | 0.615 | 2.423 | 0.036 |
| | 1990s cohort | 0.854 | 0.334 | 1.868 | 0.033 |
| | 2000s cohort | 0.858 | 0.762 | 3.114 | 0.048 |
| | Cohort trend ($\beta_2$) | −0.002 | 0.117 | 0.349 | 0.008 |
| | *t-statistic* | *−0.123* | *2.133** | 2.597** | *5.552**** |

**Table 3 continued**

| Industry | Cohort | *Production Cost* | *Soft Expense* | *Market-To-Book ratio* | *R&D* |
|---|---|---|---|---|---|
| Oil, gas, and coal | Pre-1970 firms | 1.030 | 0.178 | 1.645 | 0.006 |
| | 1970s cohort | 0.378 | 0.105 | 1.833 | 0.003 |
| | 1980s cohort | 0.374 | 0.152 | 1.979 | 0.006 |
| | 1990s cohort | 0.389 | 0.298 | 2.137 | 0.002 |
| | 2000s cohort | 0.413 | 0.523 | 2.747 | 0.005 |
| | Cohort trend ($\beta_2$) | −0.122 | 0.088 | 0.251 | 0.000 |
| | *t*-statistic | *−1.577* | *2.597*** | 4.881*** | *−0.316* |
| Chemicals and allied products | Pre-1970 firms | 0.742 | 0.288 | 1.803 | 0.049 |
| | 1970s cohort | 0.878 | 0.340 | 1.781 | 0.076 |
| | 1980s cohort | 0.727 | 0.557 | 2.152 | 0.129 |
| | 1990s cohort | 0.710 | 0.730 | 2.761 | 0.123 |
| | 2000s cohort | 0.776 | 0.903 | 4.180 | 0.137 |
| | Cohort trend ($\beta_2$) | −0.422 | 11.023 | 0.573 | 0.022 |
| | *t*-statistic | *−2.438*** | *4.833**** | 3.701** | *4.148**** |
| Telephone and television | Pre-1970 firms | 0.185 | 0.134 | 1.771 | 0.001 |
| | 1970s cohort | 0.578 | 0.538 | 1.689 | 0.001 |
| | 1980s cohort | 0.425 | 0.580 | 2.959 | 0.012 |
| | 1990s cohort | 0.363 | 0.354 | 2.534 | 0.013 |
| | 2000s cohort | 0.553 | 0.664 | 3.612 | 0.020 |
| | Cohort trend ($\beta_2$) | 0.052 | 0.088 | 0.453 | 0.005 |
| | *t*-statistic | *1.050* | *1.498* | 3.235** | *5.653**** |
| Wholesale, retail | Pre-1970 firms | 1.584 | 0.474 | 1.395 | 0.000 |
| | 1970s cohort | 1.604 | 0.530 | 2.364 | 0.004 |
| | 1980s cohort | 1.657 | 0.632 | 2.810 | 0.004 |
| | 1990s cohort | 1.725 | 0.541 | 1.883 | 0.004 |
| | 2000s cohort | 1.613 | 0.931 | 2.471 | 0.005 |
| | Cohort trend ($\beta_2$) | 0.018 | 0.092 | 0.167 | 0.001 |
| | *t-statistic* | *1.010* | *2.381*** | 0.944 | 1.970 |
| Healthcare | Pre-1970 firms | 0.365 | 0.414 | 1.407 | 0.088 |
| | 1970s cohort | 0.487 | 0.898 | 1.971 | 0.064 |
| | 1980s cohort | 0.568 | 0.886 | 1.845 | 0.123 |
| | 1990s cohort | 0.541 | 0.942 | 1.736 | 0.136 |
| | 2000s cohort | 0.402 | 1.242 | 2.831 | 0.214 |
| | Cohort trend ($\beta_2$) | 0.013 | 0.170 | 0.261 | 0.032 |
| | *t*-statistic | *0.411* | *3.703*** | 2.144* | *3.445*** |
| Other | Pre-1970 firms | 1.007 | 0.243 | 2.787 | 0.002 |
| | 1970s cohort | 0.933 | 0.426 | 3.589 | 0.004 |
| | 1980s cohort | 0.744 | 0.588 | 3.220 | 0.009 |
| | 1990s cohort | 0.738 | 0.567 | 3.536 | 0.015 |
| | 2000s cohort | 0.539 | 0.869 | 4.305 | 0.017 |
| | Cohort trend ($\beta_2$) | −0.113 | 0.139 | 0.298 | 0.004 |
| | *t*-statistic | *−7.217**** | *5.609**** | 2.750** | *8.521**** |

**Table 3 continued**

Panel B: Intangible intensity at the same stage of life cycle

| | | *Five years after listing year* | | | *Ten years after listing year* | | |
|---|---|---|---|---|---|---|---|
| Industry | | *Soft Expense* | *Market-To-Book ratio* | *R&D* | *Soft Expense* | *Market-To-Book ratio* | *R&D* |
| Consumer nondurables | Cohort trend ($\beta_2$) | 0.061 | 0.265 | 0.006 | 0.022 | 0.323 | 0.003 |
| | *t*-statistic | *2.904*** | *1.936** | *2.515*** | *5.381**** | *4.687**** | *5.462**** |
| Consumer durables | Cohort trend ($\beta_2$) | 0.078 | 0.411 | 0.018 | 0.035 | 0.250 | 0.014 |
| | *t*-statistic | *3.330*** | *3.332*** | *1.588* | *0.866* | *1.742** | *0.764* |
| Manufacturing printing | Cohort trend ($\beta_2$) | 0.063 | 0.327 | 0.017 | 0.018 | 0.232 | 0.006 |
| | *t*-statistic | *3.084*** | *3.411*** | *2.441*** | *0.671* | *2.925*** | *7.331**** |
| Oil, gas, and coal | Cohort trend ($\beta_2$) | 0.036 | 0.085 | 0.000 | 0.149 | 0.335 | -0.001 |
| | *t*-statistic | *4.887**** | *0.841* | *-0.868* | *2.962*** | *4.779**** | *-1.107* |
| Chemicals and allied | Cohort trend ($\beta_2$) | 0.094 | 0.501 | 0.662 | -0.014 | 0.453 | 0.000 |
| | *t*-statistic | *6.038**** | *3.202*** | *0.658* | *-0.347* | *3.150*** | *0.119* |
| Business equipment | Cohort trend ($\beta_2$) | 0.136 | 0.402 | 0.035 | 0.140*** | 0.411 | 0.211 |
| | *t*-statistic | *15.887**** | *3.854*** | *35.407**** | *6.172**** | *4.888**** | *2.025** |
| Telephone and television | Cohort trend ($\beta_2$) | 0.081 | 0.246 | 2.115 | 0.008 | 0.140 | 0.003 |
| | *t*-statistic | *6.550**** | *3.207*** | *1.735** | *0.374* | *0.645* | *1.721** |
| Wholesale, retail | Cohort trend ($\beta_2$) | 0.011 | 0.220 | 0.000 | 0.040 | 0.238 | 0.001 |
| | *t*-statistic | *0.650* | *2.787*** | *0.720* | *1.038* | *7.650**** | *1.593* |
| Healthcare | Cohort trend ($\beta_2$) | 0.155 | 0.441 | 0.122 | 0.254 | 0.646 | 0.083 |
| | *t*-statistic | *4.233*** | *2.703*** | *2.422*** | *3.660*** | *6.696**** | *3.806*** |
| Other | Cohort trend ($\beta_2$) | 0.097 | 0.315 | 0.004 | 0.102 | 0.464 | 0.005 |
| | *t*-statistic | *8.377**** | *3.411*** | *0.556* | *10.837**** | *6.822**** | *2.935*** |

**Table 3 continued**

Panel C: Average cost characteristics of listed firms in successive decades

| Industry | | *Soft Expense* | *Market-To-Book ratio* | *R&D* |
|---|---|---|---|---|
| Consumer nondurables | 1970–1979 | 0.387 | 1.100 | 0.004 |
| | 1980–1989 | 0.432 | 1.347 | 0.005 |
| | 1990–1999 | 0.453 | 1.706 | 0.009 |
| | 2000–2009 | 0.574 | 1.963 | 0.029 |
| Consumer durables | 1970–1979 | 0.336 | 1.196 | 0.015 |
| | 1980–1989 | 0.364 | 1.384 | 0.021 |
| | 1990–1999 | 0.402 | 1.748 | 0.037 |
| | 2000–2009 | 0.667 | 2.361 | 0.546 |
| Manufacturing and printing | 1970–1979 | 0.271 | 1.060 | 0.015 |
| | 1980–1989 | 0.319 | 1.373 | 0.021 |
| | 1990–1999 | 0.331 | 1.696 | 0.029 |
| | 2000–2009 | 0.439 | 2.077 | 0.205 |
| Oil, gas, and coal | 1970–1979 | 0.120 | 1.660 | 0.004 |
| | 1980–1989 | 0.140 | 1.692 | 0.004 |
| | 1990–1999 | 0.141 | 1.729 | 0.006 |
| | 2000–2009 | 0.380 | 2.391 | 0.203 |
| Chemicals and allied products | 1970–1979 | 0.477 | 1.538 | 0.026 |
| | 1980–1989 | 0.545 | 1.748 | 0.031 |
| | 1990–1999 | 0.464 | 2.105 | 0.043 |
| | 2000–2009 | 0.625 | 2.724 | 0.533 |
| Business equipment | 1970–1979 | 0.462 | 1.451 | 0.057 |
| | 1980–1989 | 0.567 | 1.951 | 0.089 |
| | 1990–1999 | 0.737 | 2.824 | 0.141 |
| | 2000–2009 | 0.891 | 2.920 | 0.222 |
| Telephone and television | 1970–1979 | 0.231 | 1.216 | 0.005 |
| | 1980–1989 | 0.346 | 2.033 | 0.014 |
| | 1990–1999 | 0.356 | 2.552 | 0.015 |
| | 2000–2009 | 0.538 | 2.294 | 0.563 |
| Wholesale, retail | 1970–1979 | 0.587 | 1.133 | 0.002 |
| | 1980–1989 | 0.575 | 1.436 | 0.004 |
| | 1990–1999 | 0.555 | 1.774 | 0.023 |
| | 2000–2009 | 0.634 | 1.964 | 0.006 |
| Healthcare | 1970–1979 | 0.461 | 1.989 | 0.040 |
| | 1980–1989 | 0.616 | 2.841 | 0.088 |
| | 1990–1999 | 0.697 | 3.308 | 0.136 |
| | 2000–2009 | 1.031 | 3.756 | 0.708 |
| Other | 1970–1979 | 0.264 | 1.306 | 0.007 |
| | 1980–1989 | 0.347 | 1.901 | 0.012 |
| | 1990–1999 | 0.367 | 2.144 | 0.020 |
| | 2000–2009 | 0.692 | 2.953 | 0.043 |

**Table 3 continued**

Panel D: Variation in *SoftExpense* across industries and cohorts

| | Fama and French industry code | | | | | | | | | | Standard deviation across |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Cohort | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 9 | 10 | 12 | industries |
| Pre-1970 firms | 0.396 | 0.252 | 0.206 | 0.178 | 0.288 | 0.289 | 0.134 | 0.474 | 0.414 | 0.243 | 0.110 |
| 1970s cohort | 0.401 | 0.593 | 0.275 | 0.105 | 0.340 | 0.488 | 0.538 | 0.530 | 0.898 | 0.426 | 0.211 |
| 1980s cohort | 0.640 | 0.649 | 0.615 | 0.152 | 0.557 | 0.843 | 0.580 | 0.632 | 0.886 | 0.588 | 0.196 |
| 1990s cohort | 0.451 | 0.666 | 0.334 | 0.298 | 0.730 | 0.736 | 0.354 | 0.541 | 0.942 | 0.567 | 0.209 |
| 2000s cohort | 0.921 | 1.018 | 0.762 | 0.523 | 0.903 | 1.155 | 0.664 | 0.931 | 1.242 | 0.869 | 0.215 |
| Standard deviation across cohorts | 0.224 | 0.272 | 0.238 | 0.168 | 0.259 | 0.333 | 0.212 | 0.182 | 0.297 | 0.231 | |

The average standard deviation across industries for a given cohort is 0.188. The average standard deviation across cohorts for a given industry is 0.244.

**Table 4**

Variations in measures of over production and curtailment of soft discretionary expenses

All of the firms are grouped by the Fama and French 12-industry classification. Industries representing finance firms (industry code 11) and utility firms (industry code 8) are excluded. The table presents the average attributes of each industry calculated by using all of the pooled observations from that industry from 2001 to 2010. These attributes are calculated by using the methods described in Appendix. *** indicates significance at the 1% level.

| Industry | Fama and French industry code | The average of absolute values of discretionary components: *ProductionCost* | *SoftExpense* | Test of difference |
|---|---|---|---|---|
| Consumer nondurables | 1 | 0.162 | 0.248 | |
| Consumer durables | 2 | 0.140 | 0.316 | |
| Manufacturing and printing | 3 | 0.114 | 0.227 | |
| Oil, gas, and coal | 4 | 0.131 | 0.184 | |
| Chemicals and allied products | 5 | 0.194 | 0.528 | |
| Business equipment | 6 | 0.185 | 0.393 | |
| Telephone and television | 7 | 0.137 | 0.288 | |
| Wholesale, retail | 9 | 0.177 | 0.239 | |
| Healthcare | 10 | 0.168 | 0.519 | |
| Other | 12 | 0.155 | 0.408 | |
| Mean | | 0.156 | 0.335 | −0.179*** |
| Standard deviation | | 0.026 | 0.122 | −0.096*** |
| Range | | 0.079 | 0.344 | |

Correlation between the nondiscretionary component and the absolute value of the discretionary component of *ProductionCost* is 0.197 ($p$-value of 0.58). Correlation between the nondiscretionary component and the absolute value of the discretionary component *SoftExpense* is 0.949 ($p$-value < 0.01).

**Table 5**

Trends in measures of real earnings management and financial characteristics of successive cohorts of listed firms by Fama and French 12-industry classification

The first year in which a firm's data are available in Compustat is the listing year. All firms with listing year after 2009 are excluded (Srivastava 2014). All firms with a listing year before 1970 are classified as Pre-1970 firms. All of the cohorts listed in a common decade constitute a cohort of new firms. Consequently, all of the firms are divided into Pre-1970 firms or a cohort from the 1970s, 1980s, 1990s, or 2000s. These five cohorts are assigned *CohortDummy* of 0, 1, 2, 3, and 4, respectively. All of the firms are grouped by the Fama and French 12-industry classification. Industries representing the finance (industry code 11) and utility firms (industry code 8) are excluded. All variables are defined in the Appendix. For Panels A and B, the average characteristic of each cohort for each Fama and French industry is calculated using pooled data from 2001 to 2010. The cohort trend ($\beta_2$) is calculated using the following equation and five observations from five cohorts: $AverageCohortCharacteristic = \beta_1 + \beta_2 \times CohortDummy + \varepsilon$. For Panels C and D, the average characteristic is first calculated by cohort, Fama−French industry, and year. Then cohort trend is calculated for each industry and year. I next examine whether the average of ten cohort trends for each industry is significantly different from zero (Fama and MacBeth 1973). I also examine whether the average of ten industry cohort trends in a year is significantly different from zero.*, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively, on a one-tailed basis.

Panel A: Cohort trends in real earnings measures by industries

| | | Discretionary components | | Nondiscretionary components | |
|---|---|---|---|---|---|
| Industry | | *ProductionCost* | *SoftExpense* | *ProductionCost* | *SoftExpense* |
| Consumer nondurables | Cohort trend ($\beta_2$) | 0.006 | 0.031 | −0.025 | 0.059 |
| | *t*-statistic | *0.530* | *1.975** | *−0.682* | *1.884** |
| Consumer durables | Cohort trend ($\beta_2$) | −0.008 | 0.051 | 0.005 | 0.093 |
| | *t*-statistic | *−1.117* | *2.380*** | *0.286* | *2.132** |
| Manufacturing printing | Cohort trend ($\beta_2$) | 0.004 | 0.037 | −0.008 | 0.060 |
| | *t*-statistic | *1.563* | *3.723*** | *−0.398* | *1.422* |
| Oil, gas, and coal | Cohort trend ($\beta_2$) | 0.000 | 0.019 | −0.124 | 0.065 |
| | *t*-statistic | *0.008* | *1.575* | *−1.716** | *3.168*** |
| Chemicals and allied products | Cohort trend ($\beta_2$) | 0.003 | 0.033 | −0.014 | 0.100 |
| | *t*-statistic | *0.291* | *2.366*** | *−0.977* | *5.357**** |
| Business equipment | Cohort trend ($\beta_2$) | −0.028 | 0.104 | −0.021 | 0.077 |
| | *t*-statistic | *−3.081*** | *6.838**** | *−0.870* | *2.773*** |
| Telephone and television | Cohort trend ($\beta_2$) | 0.000 | 0.029 | 0.050 | 0.043 |
| | *t*-statistic | *0.038* | *1.154* | *1.104* | *0.808* |
| Wholesale, retail | Cohort trend ($\beta_2$) | 0.005 | 0.023 | 0.010 | 0.060 |
| | *t*-statistic | *0.784* | *2.008** | *0.579* | *2.218** |
| Healthcare | Cohort trend ($\beta_2$) | 0.011 | 0.114 | 0.001 | 0.043 |
| | *t*-statistic | *1.307* | *10.038**** | *0.040* | *1.491* |
| Other | Cohort trend ($\beta_2$) | −0.021 | 0.068 | −0.092 | 0.064 |
| | *t*-statistic | *−7.746**** | *6.986**** | *−5.523**** | *3.304*** |

**Table 5 continued**

Panel B: Cohort trends in financial characteristics by industries using pooled data from 2001 to 2010.

| | | *Accruals* | | Financial characteristics | | |
|---|---|---|---|---|---|---|
| Industry | | Performance-matched nondiscretionary component | Performance-matched discretionary component | *CFO* | *Earnings-To-Price ratio* | *Sales Growth* |
| Consumer nondurables | Cohort trend ($\beta_2$) | −0.011 | 0.007 | −0.431 | −0.084 | 0.031 |
| | *t*-statistic | *−1.801** | *1.934** | *−1.688** | *−2.534*** | *3.215*** |
| Consumer durables | Cohort trend ($\beta_2$) | −0.018 | 0.014 | −0.929 | 0.021 | 0.059 |
| | *t*-statistic | *−5.252**** | *6.645**** | *−3.121*** | *0.188* | *3.133*** |
| Manufacturing and printing | Cohort trend ($\beta_2$) | −0.010 | 0.006 | −0.255 | −0.059 | 0.037 |
| | *t*-statistic | *−1.908** | *3.708*** | *−5.696**** | *−1.969** | *2.779*** |
| Oil, gas, and coal | Cohort trend ($\beta_2$) | −0.016 | −0.003 | −0.326 | −0.116 | 0.061 |
| | *t*-statistic | *−2.789*** | *−1.204* | *−2.610*** | *−3.852*** | *2.965*** |
| Chemicals and allied products | Cohort trend ($\beta_2$) | −0.018 | 0.009 | −0.656 | −0.087 | 0.044 |
| | *t*-statistic | *−8.238**** | *6.279**** | *−2.840*** | *−1.718** | *2.860*** |
| Business equipment | Cohort trend ($\beta_2$) | −0.017 | 0.004 | −0.112 | −0.073 | 0.050 |
| | *t*-statistic | *−3.475*** | *0.996* | *−0.489* | *−2.811*** | *2.839*** |
| Telephone and television | Cohort trend ($\beta_2$) | −0.013 | −0.001 | 0.016 | −0.146 | 0.047 |
| | *t*-statistic | *−1.809** | *−0.130* | *0.035* | *−1.094* | *2.267** |
| Wholesale, retail | Cohort trend ($\beta_2$) | −0.005 | 0.005 | −0.325 | −0.060 | 0.037 |
| | *t*-statistic | *−1.756** | *1.968** | *−0.959* | *−2.030** | *2.721*** |
| Healthcare | Cohort trend ($\beta_2$) | −0.015 | 0.012 | −0.407 | −0.104 | 0.054 |
| | *t*-statistic | *−1.992** | *3.858*** | *−3.078*** | *−5.816**** | *3.321*** |
| Other | Cohort trend ($\beta_2$) | −0.018 | 0.010 | −0.295 | −0.004 | 0.041 |
| | *t*-statistic | *−3.416*** | *4.480*** | *-1.787** | *−0.045* | *6.324**** |

**Table 5 continued**

Panel C: Cohort trend for discretionary components of *SoftExpense* for each Fama and French industry and year

| Industry | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | Mean | *t*-statistic |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Consumer nondurables | 0.030 | 0.063 | 0.050 | 0.087 | 0.044 | 0.032 | 0.004 | 0.004 | 0.001 | 0.010 | 0.033 | *3.580* |
| Consumer durables | 0.038 | 0.030 | 0.103 | 0.077 | −0.023 | 0.082 | 0.052 | 0.053 | 0.073 | 0.063 | 0.055 | *5.000* |
| Manufacturing and printing | 0.027 | 0.056 | 0.045 | 0.062 | 0.035 | 0.038 | 0.037 | 0.021 | 0.022 | 0.028 | 0.037 | *8.660* |
| Oil, gas, and coal | 0.026 | 0.069 | 0.056 | 0.023 | 0.005 | −0.024 | 0.015 | 0.007 | 0.011 | 0.022 | 0.021 | *2.560* |
| Chemicals and allied products | 0.079 | 0.077 | 0.073 | 0.019 | 0.047 | 0.034 | 0.017 | 0.010 | 0.008 | 0.012 | 0.038 | *4.080* |
| Business equipment | 0.088 | 0.092 | 0.113 | 0.158 | 0.100 | 0.113 | 0.109 | 0.086 | 0.081 | 0.093 | 0.103 | *14.570* |
| Telephone and television | 0.048 | 0.055 | 0.031 | 0.043 | −0.013 | 0.050 | 0.036 | 0.005 | 0.045 | −0.017 | 0.028 | *3.340* |
| Wholesale, retail | 0.033 | 0.043 | 0.044 | 0.067 | 0.036 | 0.022 | 0.015 | −0.006 | −0.011 | −0.006 | 0.024 | *2.930* |
| Healthcare | 0.109 | 0.096 | 0.106 | 0.187 | 0.113 | 0.111 | 0.108 | 0.102 | 0.085 | 0.143 | 0.116 | *12.700* |
| Other | 0.064 | 0.087 | 0.101 | 0.110 | 0.098 | 0.053 | 0.059 | 0.043 | 0.042 | 0.044 | 0.070 | *8.410* |
| Mean | 0.054 | 0.067 | 0.072 | 0.083 | 0.044 | 0.051 | 0.045 | 0.033 | 0.036 | 0.039 | | |
| *t*-statistic | *5.860* | *9.710* | *7.390* | *4.780* | *2.960* | *3.890* | *3.800* | *2.750* | *3.240* | *2.560* | | |

Panel D: Cohort trend for nondiscretionary components of *SoftExpense* for each Fama and French industry and year

| Industry | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | Mean | *t*-statistic |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Consumer nondurables | 0.076 | 0.052 | 0.035 | 0.055 | 0.079 | 0.033 | -0.012 | 0.125 | 0.023 | 0.011 | 0.067 | *3.040* |
| Consumer durables | 0.079 | 0.050 | 0.067 | 0.090 | 0.052 | 0.058 | 0.020 | 0.075 | 0.024 | 0.073 | 0.096 | *5.410* |
| Manufacturing and printing | 0.164 | 0.157 | 0.097 | 0.163 | 0.128 | 0.148 | 0.057 | 0.200 | 0.053 | 0.125 | 0.062 | *5.180* |
| Oil, gas, and coal | 0.205 | 0.145 | 0.102 | 0.209 | 0.115 | 0.149 | 0.137 | 0.150 | 0.096 | 0.175 | 0.078 | *3.690* |
| Chemicals and allied | 0.071 | 0.194 | 0.119 | 0.125 | 0.142 | 0.127 | 0.060 | 0.100 | 0.048 | 0.164 | 0.099 | *10.640* |
| Business equipment | 0.029 | 0.119 | 0.086 | 0.037 | 0.134 | 0.081 | 0.105 | 0.032 | 0.063 | 0.090 | 0.076 | *5.030* |
| Telephone and television | 0.016 | 0.098 | 0.046 | 0.021 | 0.092 | 0.044 | 0.045 | 0.011 | 0.044 | 0.061 | 0.039 | *2.140* |
| Wholesale, retail | 0.023 | 0.053 | 0.015 | 0.022 | 0.070 | 0.035 | 0.052 | -0.005 | 0.022 | 0.023 | 0.069 | *3.040* |
| Healthcare | -0.001 | 0.028 | 0.023 | 0.031 | 0.088 | 0.035 | -0.033 | 0.004 | 0.021 | 0.012 | 0.044 | *5.880* |
| Other | 0.003 | 0.060 | 0.026 | 0.027 | 0.091 | 0.050 | -0.042 | 0.002 | 0.041 | -0.010 | 0.073 | *3.500* |
| Mean | 0.067 | 0.096 | 0.062 | 0.078 | 0.099 | 0.076 | 0.039 | 0.069 | 0.044 | 0.067 | | |
| *t*-statistic | *3.040* | *5.410* | *5.180* | *3.690* | *10.640* | *5.030* | *2.140* | *3.040* | *5.880* | *3.040* | | |

**Table 6**

Trends in measures of financial distress and the need for external funds of successive cohorts of listed firms

The first year in which a firm's data are available in Compustat is the listing year. All firms with listing year after 2009 are excluded (Srivastava 2014). The remaining firms are divided into five listing cohorts. All firms with a listing year before 1970 are classified as Pre-1970 firms. The remaining firms are classified as new firms. All of the cohorts listed in a common decade constitute a cohort of new firms. Consequently, all of the firms are divided into Pre-1970 firms or a cohort from the 1970s, 1980s, 1990s, or 2000s. These five cohorts are assigned *CohortDummy* of 0, 1, 2, 3, and 4, respectively. The numbers of observations in each cohort−year are described in Table 1. All variables are defined in the Appendix. The average characteristics of each cohort are calculated using pooled data from 2001 to 2010. The cohort trend is calculated using the following equation and f five observations from five cohorts: $AverageCohortCharacteristic = \beta_1 + \beta_2 \times CohortDummy + \varepsilon$. $\beta_2$ represents the trend in average firm characteristics across successive cohorts. For Panel B, all of the firms are grouped by the Fama and French 12-industry classification. Industries representing the finance (industry code 11) and utility firms (industry code 8) are excluded. All variables are defined in the Appendix. The average characteristic of each cohort for each industry is calculated using pooled data from 2001 to 2010. Then cohort trend is calculated for each using its five cohort observations *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively, on a one-tailed basis.

Panel A: Trends in measures of financial distress and the need for external funds

| Cohort | Prior loss | Altman's bankruptcy | Shumway's bankruptcy | Significant debt or equity raised |
|---|---|---|---|---|
| Pre-1970 firms | 29.16% | 18.28% | 0.02% | 12.38% |
| 1970s cohort | 39.24% | 25.12% | 0.10% | 16.37% |
| 1980s cohort | 49.97% | 33.37% | 0.26% | 21.03% |
| 1990s cohort | 56.17% | 39.37% | 0.43% | 22.97% |
| 2000s cohort | 67.13% | 44.65% | 0.55% | 33.22% |
| Cohort trend ($\beta_2$) | 0.093 | 0.067 | 0.001 | 0.048 |
| *t*-statistic | 22.24*** | 21.50*** | 18.25*** | 6.68*** |

**Table 6 continued**

Trends in measures of financial distress and the need for external funds of successive cohorts of listed firms by Fama and French 12-industry classification

Panel B: Trends in measures of financial distress and the need for external funds by industry

| Industry | | Prior loss | Altman's bankruptcy | Shumway's bankruptcy | Significant debt or equity raised |
|---|---|---|---|---|---|
| Consumer nondurables | Cohort trend ($\beta_2$) | *0.056* | *0.078* | *0.000* | *0.024* |
| | *t*-statistic | *2.622*** | *5.165**** | *2.964*** | *1.768** |
| Consumer durables | Cohort trend ($\beta_2$) | *0.045* | *0.041* | *0.000* | *0.041* |
| | *t*-statistic | *1.605* | *1.381* | *1.078* | *2.146** |
| Manufacturing printing | Cohort trend ($\beta_2$) | *0.065* | *0.053* | *0.000* | *0.039* |
| | *t*-statistic | *3.809*** | *2.316** | *1.860** | *5.103**** |
| Oil, gas, and coal | Cohort trend ($\beta_2$) | *0.101* | *0.084* | *0.000* | *0.066* |
| | *t*-statistic | *3.947*** | *3.415*** | *−0.265* | *11.449**** |
| Chemicals and allied products | Cohort trend ($\beta_2$) | *0.099* | *0.083* | *0.000* | *0.056* |
| | *t*-statistic | *7.019**** | *7.178**** | *1.157* | *2.253** |
| Business equipment | Cohort trend ($\beta_2$) | *0.097* | *0.079* | *0.000* | *0.041* |
| | *t*-statistic | *9.583**** | *5.315**** | *4.668**** | *5.284**** |
| Telephone and television | Cohort trend ($\beta_2$) | *0.029* | *−0.036* | *0.000* | *−0.012* |
| | *t*-statistic | *1.549* | *−3.460*** | *−0.341* | *−1.088* |
| Wholesale, retail | Cohort trend ($\beta_2$) | *0.047* | *0.053* | *0.000* | *0.039* |
| | *t*-statistic | *7.052**** | *4.863**** | *12.427**** | *4.004*** |
| Healthcare | Cohort trend ($\beta_2$) | *0.151* | *0.085* | *0.000* | *0.070* |
| | *t*-statistic | *5.923**** | *3.342*** | *1.593* | *3.746*** |
| Other | Cohort trend ($\beta_2$) | *0.069* | *0.020* | *0.000* | *0.061* |
| | *t*-statistic | *5.918**** | *2.433*** | *2.332** | *7.845**** |

**Table 7**

Correlation between measures of real earnings management and measures of financial distress

The first year in which a firm's data are available in Compustat is the listing year. All firms with listing year after 2009 are excluded (Srivastava 2014). The remaining firms are divided into five listing cohorts. All firms with a listing year before 1970 are classified as Pre-1970 firms. The remaining firms are classified as new firms. All of the cohorts listed in a common decade constitute a cohort of new firms. Consequently, all of the firms are divided into Pre-1970 firms or a cohort from the 1970s, 1980s, 1990s, or 2000s. Fifty averages of each characteristic are calculated using pooled observations from 50 industry-cohorts (ten industries × five cohorts). Panel A examines correlations between measures of financial distress and measures of real earnings management. Panel B examines correlations between measures of financial distress and innate costs (the nondiscretionary components). All variables are defined in the Appendix. Correlations significant at *p*-levels of 0.10, 0.05, and 0.01 are indicated by *, **, and ***, respectively.

Panel A: Discretionary components of earnings management

| | | Pearson correlation | | | | | |
|---|---|---|---|---|---|---|---|
| | N=50 industry cohorts averages | Measures of real earnings management | | Measures of financial distress | | | |
| | | Discretionary *ProductionCost* | Discretionary *SoftExpense* | Prior loss | Altman's bankruptcy | Shumway's bankruptcy | Significant debt or equity raised |
| Spearman rank correlation | Discretionary *ProductionCost* | | −0.589*** | −0.017 | 0.014 | −0.269* | 0.011 |
| | Discretionary *SoftExpense* | −0.503*** | | 0.437*** | 0.229 | 0.225 | 0.394*** |
| | Prior loss | −0.117 | 0.404*** | | 0.795*** | 0.438*** | 0.695*** |
| | Altman's bankruptcy | −0.048 | 0.268* | 0.867*** | | 0.508*** | 0.617*** |
| | Shumway's bankruptcy | −0.307** | 0.425*** | 0.728*** | 0.707*** | | 0.216 |
| | Significant debt or equity raised | −0.104 | 0.418*** | 0.675*** | 0.718*** | 0.492*** | |

**Table 7 continued**

Panel B: Nondiscretionary components of costs

| N=50 industry cohorts | Innate costs: Nondiscretionary *ProductionCost* | Innate costs: Nondiscretionary *SoftExpense* | Measures of financial distress: Prior loss | Measures of financial distress: Altman's bankruptcy | Measures of financial distress: Shumway's bankruptcy | Measures of financial distress: Significant debt or equity raised |
|---|---|---|---|---|---|---|
| Nondiscretionary *ProductionCost* | | −0.006 | −0.427*** | −0.586*** | −0.343** | −0.370*** |
| Nondiscretionary *SoftExpense* | −0.082 | | 0.420*** | 0.052 | 0.075 | 0.334** |
| Prior loss | −0.518*** | 0.410*** | | 0.795*** | 0.438*** | 0.695*** |
| Altman's bankruptcy | −0.622*** | 0.143 | 0.867*** | | 0.508*** | 0.617*** |
| Shumway's bankruptcy | −0.470*** | 0.160 | 0.728*** | 0.707*** | | 0.216 |
| Significant debt or equity raised | −0.454*** | 0.306** | 0.675*** | 0.718*** | 0.492*** | |

Pearson correlation (above diagonal); Spearman rank correlation (below diagonal)

**Table 8**

Trends in modified measures of soft expense manipulation across successive cohorts of listed firms

The first year in which a firm's data are available in Compustat is the listing year. All firms with listing year after 2009 are excluded (Srivastava 2014). The remaining firms are divided into five listing cohorts. All firms with a listing year before 1970 are classified as Pre-1970 firms. The remaining firms are classified as new firms. All of the cohorts listed in a common decade constitute a cohort of new firms. Consequently, all of the firms are divided into Pre-1970 firms or a cohort from the 1970s, 1980s, 1990s, or 2000s. These five cohorts are assigned *CohortDummy* of 0, 1, 2, 3, and 4, respectively. All variables are defined in the Appendix. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively, on a one-tailed basis. For Panel A, the number of observations in each cohort-year is described in Table 1. The average characteristics of each cohort are calculated using pooled data from 2001 to 2010. The cohort trend is calculated using the following equation and five observations of five observations from five cohorts: $AverageCohortCharacteristic = \beta_1 + \beta_2 \times CohortDummy + \varepsilon$. $\beta_2$ represents the trend in average firm characteristics across successive cohorts. For Panel B, all of the firms are sorted by the Fama and French 12-industry method. Industries representing finance firms (industry code 11) and utility firms (industry code 8) are excluded. The average characteristic of each cohort for each Fama and French industry is calculated using pooled data from 2001 to 2010. The cohort trend is calculated for each Fama and French industry using the five observations from its five cohorts. $\beta_2$ represents the trend in average firm characteristics across successive cohorts in each industry..

Panel A: Trend in measures of discretionary *SoftExpense*

| | Discretionary *SoftExpense* | | | |
|---|---|---|---|---|
| Cohort | *ListVintage*-controlled measure of discretionary *SoftExpense* | *ListVintage*-matched measure of discretionary *SoftExpense* | *MarketToBook*-controlled modified measure of discretionary *SoftExpense* | *MarketToBook*-matched measure of discretionary *SoftExpense* |
| Pre-1970 firms | 0.029 | −0.003 | −0.095 | −0.073 |
| 1970s cohort | −0.003 | −0.003 | −0.076 | −0.074 |
| 1980s cohort | −0.006 | −0.007 | −0.047 | −0.029 |
| 1990s cohort | −0.037 | −0.008 | −0.010 | 0.005 |
| 2000s cohort | 0.016 | −0.005 | 0.035 | 0.037 |
| Cohort trend ($\beta_2$) | −0.006 | −0.001 | 0.033 | 0.030 |
| *t*-statistic | *−0.691* | *−1.472* | *11.011**** | *7.433**** |

**Table 8 continued**

Trends in modified measures of soft expense manipulation across successive cohorts of listed firms by Fama and French 12-industry classification

Panel B: Trend in discretionary *SoftExpense* by industry classification

| Industry | | *ListVintage*-controlled measure of discretionary *SoftExpense* | *ListVintage*-matched measure of discretionary *SoftExpense* | *MarketToBook*-controlled modified measure of discretionary *SoftExpense* | *MarketToBook*-matched measure of discretionary *SoftExpense* |
|---|---|---|---|---|---|
| Consumer nondurables | Cohort trend ($\beta_2$) | −0.002 | 0.005 | 0.018 | 0.013 |
| | *t*-statistic | *−0.126* | *0.549* | *1.510* | *1.911** |
| Consumer durables | Cohort trend ($\beta_2$) | −0.005 | −0.013 | 0.018 | 0.016 |
| | *t*-statistic | *−0.226* | *−0.713* | *1.337* | *0.616* |
| Manufacturing and printing | Cohort trend ($\beta_2$) | −0.009 | −0.006 | 0.018 | 0.017 |
| | *t*-statistic | *−0.719* | *−1.028* | *3.017*** | *2.667*** |
| Oil, gas, and coal | Cohort trend ($\beta_2$) | −0.004 | 0.002 | 0.009 | 0.011 |
| | *t*-statistic | *−0.244* | *0.789* | *0.701* | *0.596* |
| Chemicals and allied products | Cohort trend ($\beta_2$) | −0.070 | −0.029 | 0.001 | −0.032 |
| | *t*-statistic | *−5.691**** | *−1.301* | *0.052* | *−1.386* |
| Business equipment | Cohort trend ($\beta_2$) | 0.005 | −0.001 | 0.068 | 0.063 |
| | *t*-statistic | *0.368* | *−0.120* | *6.205**** | *5.769**** |
| Telephone and television | Cohort trend ($\beta_2$) | −0.020 | −0.007 | 0.020 | 0.030 |
| | *t*-statistic | *−0.771* | *−1.960** | *2.065** | *0.628* |
| Wholesale, retail | Cohort trend ($\beta_2$) | 0.001 | −0.009 | 0.010 | 0.006 |
| | *t*-statistic | *0.054* | *−2.979*** | *1.048* | *0.503* |
| Healthcare | Cohort trend ($\beta_2$) | −0.022 | −0.008 | 0.087 | 0.077 |
| | *t*-statistic | *−1.314* | *−0.506* | *15.236**** | *8.799**** |
| Other | Cohort trend ($\beta_2$) | −0.039 | 0.000 | 0.040 | 0.048 |
| | *t*-statistic | *−2.196** | *−0.041* | *4.252*** | *7.175**** |

**Table 9**

Correlation between modified measures of real earnings management and measures of financial distress

The first year in which a firm's data are available in Compustat is the listing year. All firms with listing year after 2009 are excluded (Srivastava 2014). The remaining firms are divided into five listing cohorts. All firms with a listing year before 1970 are classified as Pre-1970 firms. The remaining firms are classified as new firms. All of the cohorts listed in a common decade constitute a cohort of new firms. Consequently, all of the firms are divided into Pre-1970 firms or a cohort from the 1970s, 1980s, 1990s, or 2000s. All variables are defined in Appendix. Fifty averages of each characteristic are calculated using pooled observations from 50 industry-cohorts (ten industries × five cohorts). This table examines correlations between measures of financial distress and modified measures of real earnings management. Correlations significant at *p*-levels of 0.10, 0.05, and 0.01 are indicated with *, **, and ***, respectively.

Panel A: Modified measure of discretionary *SoftExpense* calculated by controlling for listing vintage in the first-stage regression

| N=50 industry cohorts averages | | Pearson correlation | | | |
|---|---|---|---|---|---|
| | | | Measures of financial distress | | |
| Spearman rank correlation | Discretionary *SoftExpense* | Prior loss | Altman's bankruptcy | Shumway's bankruptcy | Significant debt or equity raised |
| Discretionary *SoftExpense* | | −0.089 | −0.072 | 0.081 | −0.241* |
| Prior loss | 0.013 | | 0.795*** | 0.438*** | 0.695*** |
| Altman's bankruptcy | −0.044 | 0.867*** | | 0.508*** | 0.617*** |
| Shumway's bankruptcy | −0.014 | 0.728*** | 0.707*** | | 0.216 |
| Significant debt or equity raised | −0.097 | 0.675*** | 0.718*** | 0.492*** | |

Panel B: Modified measure of discretionary *SoftExpense* calculated by using a control-group approach matched on listing vintage

| N=50 industry cohorts averages | | Pearson correlation | | | |
|---|---|---|---|---|---|
| | | | Measures of financial distress | | |
| Spearman rank correlation | Discretionary *SoftExpense* | Prior loss | Altman's bankruptcy | Shumway's bankruptcy | Significant debt or equity raised |
| Discretionary *SoftExpense* | | −0.038 | −0.091 | 0.226 | −0.192 |
| Prior loss | 0.005 | | 0.795*** | 0.438*** | 0.695*** |
| Altman's bankruptcy | −0.069 | 0.867*** | | 0.508*** | 0.617*** |
| Shumway's bankruptcy | 0.178 | 0.728*** | 0.707*** | | 0.216 |
| Significant debt or equity raised | −0.086 | 0.675*** | 0.718*** | 0.492*** | |

**Table 9 continued**

Correlation between modified measures of real earnings management and measures of financial distress

Panel C: Modified measure of discretionary *SoftExpense* calculated after controlling for market-to-book ratio in the first-stage regression

N=50 industry cohorts averages. Above diagonal: Pearson correlation. Below diagonal: Spearman rank correlation.

| | Discretionary *SoftExpense* | Prior loss | Altman's bankruptcy | Shumway's bankruptcy | Significant debt or equity raised |
|---|---|---|---|---|---|
| Discretionary *SoftExpense* | | 0.376*** | 0.167 | 0.242* | 0.290** |
| Prior loss | 0.324** | | 0.795 | 0.438*** | 0.695 |
| Altman's bankruptcy | 0.191 | 0.867*** | | 0.508*** | 0.617 |
| Shumway's bankruptcy | 0.430*** | 0.728*** | 0.707*** | | 0.216 |
| Significant debt or equity raised | 0.322** | 0.675*** | 0.718*** | 0.492*** | |

(Columns "Prior loss" through "Significant debt or equity raised": Measures of financial distress.)

Panel D: Modified measure of discretionary *SoftExpense* calculated by using a control-group approach matched on market-to-book ratio

N=50 industry cohorts averages. Above diagonal: Pearson correlation. Below diagonal: Spearman rank correlation.

| | Discretionary *SoftExpense* | Prior loss | Altman's bankruptcy | Shumway's bankruptcy | Significant debt or equity raised |
|---|---|---|---|---|---|
| Discretionary *SoftExpense* | | 0.320** | 0.132 | −0.010 | 0.249* |
| Prior loss | 0.292** | | 0.795 | 0.438*** | 0.695 |
| Altman's bankruptcy | 0.134 | 0.867*** | | 0.508*** | 0.617 |
| Shumway's bankruptcy | 0.273* | 0.728*** | 0.707*** | | 0.216 |
| Significant debt or equity raised | 0.278* | 0.675*** | 0.718*** | 0.492*** | |

(Columns "Prior loss" through "Significant debt or equity raised": Measures of financial distress.)