Why have measures of earnings quality changed over time? A competing narrative

Catalin Starica · Jian Kang

Abstract We contribute to the debate on the reason for the decline in earnings quality (EQ) documented by prior literature. We dissent from Srivastava (2014)’s conclusion that “each new cohort of listed firms exhibits lower earnings quality than its predecessors, mainly because of higher intangible intensity”. Instead, we argue that the downward trend in EQ measures is explained by changes in firms’ profitability, growth and risk associated with “broadening of the kinds of firms publicly traded” (Fama and French (2004)) and “an increasingly competitive environment” (Irvine and Pontiff (2009)). The association of intangible intensity to EQ measures is spurious and disappears when controlling for the mentioned firm’s characteristics.

Keywords Earnings quality · expectations formation pertinence · non-linear association · non-parametric regression · cohorts

Catalin Starica
School of Economics and Business, University of Neuchâtel, Switzerland. E-mail: catalin.starica@unine.ch

Jian Kang
Coordinated Innovation Center for Computable Modeling in Management Science, Tianjin University of Finance and Economics, China. E-mail: jian.kang@tjufe.edu.cn
1 Introduction

Previous literature documented sustained decline of earnings quality (EQ) over the last few decades. There is, however, disagreement about the reasons for this phenomenon.

A seminal contribution, Srivastava (2014) sheds light on the nature of and the possible explanation for the decline in three commonly used EQ measures: earnings volatility, matching of revenues and expenses, and value relevance of earnings. First, it argues that “the bulk of the changes in EQ measures over the last 40 years is due to the assimilation of newly listed firms into the firm population and not to changes in the EQ measures of existing firms” (the “new listing” phenomenon). Second, it documents increasing intangible intensity for successive cohorts of newly listed firms and concludes that “the biggest factor behind the new-list effect is the widening gap between the intangible intensities of the new- and seasoned-firm segments” (page 198).

This identification is at odds with other references in the literature. Irvine and Pontiff (2009) documents a steady increase\(^1\) of earnings volatility over the period 1970-2005 and associates the trend to an “increasingly competitive environment in which firms have less market power”. Donelson et al (2011) argues that the decline in matching of revenues and expenses is “primarily attributable to an increase in the incidence of large special items” associated to “the well-documented increase in competition in the U.S. economy over the last four decades”.

Less directly related, Bushman et al (2016) argues that the correlation between accruals and cash flows, a fourth EQ measure, has “dramatically

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\(^1\) Their estimates put the annual growth in earnings volatility at an impressive rate of 16%. 

diminished in magnitude over the past half century” and concludes that “one-
time and non-operating items and loss firms are mostly responsible for the 
attenuation in the overall correlation between accruals and cash”. Moreover,
different from the conclusion of Srivastava (2014), it finds that “the coefficient 
on $SG&A$ intensity remains [...] insignificant” in the multiple regression used 
to disentangle the contribution of competing firm characteristics. Its effect 
“is subsumed by other explanatory variables”.

In this paper we provide an unifying perspective on these apparently con-
trasting findings on the relation between declining EQ measures and changing 
firms’ fundamental characteristics. First, we bring evidence that the increase 
in the frequency of loss firm-years, one of the two explanatory variables in 
Bushman et al (2016), is largely responsible for the decrease of the three 
EQ measures in Srivastava (2014). Second, we argue that the frequency of 
negative earnings is associated to one-time reported losses but not to expens-
ing of intangible outlays. Third, we show that, while significantly negative 
when considered alone, the association of intangible intensity with the three 
EQ proxies is strongly reduced or disappears completely when controlling for 
the frequency of reporting negative earnings. This, together with the previ-
ous finding, implies that the effect of intangibles intensity on the three EQ 
measures in Srivastava (2014) is subsumed by other explanatory variables. 
This finding matches the results in Bushman et al (2016) on the correlation 
between cash flows and accruals. In statistical terms, Srivastava (2014)’s iden-
tification of the widening gap between the intangible intensities of the new-
and seasoned-firm segments as the biggest factor behind the decline of the 
EQ measures is the result of an analysis affected by omitted variable bias.

A second important contribution of our paper consists in identifying the 
fundamental firm characteristics whose evolution explains (practically all of)
the decline in the three EQ measures in Srivastava (2014). These characteristics are related to profitability, growth, economic riskiness, and the variability of non-timing-related accruals. In particular we confirm the conjecture of Bushman et al (2016) which states: “It is possible that our documented attenuation in the accrual cash flow relation and the factors contributing to that attenuation” (that is, increases in one-time and non-operating items and in firms reporting losses) “may be able to explain, in full or in part,” the decline over time in the value relevance of earnings (Collins et al (1997)).

Our aims are accomplished in three steps. First, we document the “new-listing” nature\(^2\) of the changes in fundamental characteristics related to profitability and economic riskiness of listed firms over the past 40 years.

Second, we establish the level of association between the measures of EQ and these firm characteristics. We show that the association of intangible intensity with EQ measures is largely spurious and mostly disappears when we control for the frequency of loss firm-years.

Third, in a time series analysis, we demonstrate the impact of the findings in the previous two steps on explaining the time evolution of the three EQ measures. The cohort differences in the EQ measures are strongly reduced or practically eliminated once we control for the fundamental firm characteristics identified as significant in the second step. In contrast to that, they are only slightly reduced if we control just for intangible intensity.

If the narrative underlying Srivastava (2014) is that the evolution towards a “21st century firm” characterized by higher knowledge intensity is responsible for the ever lower levels of earnings quality, our account associates the\(^2\) We identify a “new listing” effect when the overall sample evolution is due to the arrival to the market of successive cohort with ever higher/lower levels of the characteristic of interest while individual cohorts roughly evolve around their initial level through time, without an obvious trend (see also section 3.1).
Which of the two is a more truthful explanation for the decline of the EQ measures is not only a question for academic debate as the two alternative narratives pass contrasting judgments on the accounting standards. If the increase in the intangible intensity is at the bottom of the decline in EQ, the trend might be taken as proof of the failure of accounting reporting to appropriately record and quantify the risks and returns of intangible investments, a particularly severe implication. If, contrary, the explanation for lessening of EQ lies with the facilitated access to public equity financing of weaker firms and firms whose expected payoffs are further in the future, the downwards trend is evidence of a well-functioning reporting system that recognizes and measures the increasing weaknesses in the firm population.

The comprehensive analysis we conduct is made possible by two novel methodological aspects. The first consists in re-defining the EQ measure that quantifies the association between the prices and earnings. Srivastava (2014) measures this association by the adjusted-$R^2$ of the regression of annual stock returns on the levels of, and changes in, annual earnings (Easton and Harris (1991), Lev and Zarowin (1999)). Such a measure is not suited for the conditional analysis needed to disentangle the impact of different changing fundamental characteristics that compete to explaining the decreased earnings association with prices. Moreover, Kang and Starica (2016) argue that
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neither the price level regressions nor the returns earnings regressions are necessarily able to truthfully infer the economic relation in the Residual Income (RI) valuation model, as both are empirical specifications of a model representation that is not necessary a regression.

As a remedy, we use the expectation formation pertinence (EFP) research design (Kang and Starica (2016)) which decomposes prices into a valuation incorporating expectations of future abnormal earnings formed only on the basis of the level of reported earnings and an investors’ adjustment reflecting other information (than reported earnings). In valuation terms, investors’ adjustment corresponds to the error of a valuation informed only by the level of earnings. The association measure of this research design is the absolute valuation error and amounts to the proportion of the price corresponding to earnings expectations shaped by information other than the current values of earnings. This measure can be consistently estimated from the data and is amenable to a multivariate conditional regression analysis: one can directly regress it on several fundamental firm characteristics so addressing the omitted variable bias in individual analyses.

The second methodological aspect concerns the implementation of the conditional analysis of the association between the EQ measures and various fundamental firm characteristics in the second and third steps of our investigation. As the assumption of a linear relation between the EQ quality measures and fundamental firm characteristics is not plausible we make an atypical use of the linear regression as a tool for testing differences in mean. Concretely, we convert the numerical values of firms characteristics in level

3 These include intangible intensity, ROA, frequency of reporting negative earnings, size, cash flow volatility, or TA growth.
indicators and test if firms with values under/above the reference level have lower/higher associated EQ measures.

2 Motivation

2.1 Changes in the fundamental characteristics of U.S. firms.

The growing body of accounting literature that investigates the impact of the recent economic developments in the U.S. business environment has documented several mechanisms of change with clearly defined impact on the fundamentals of firms over the last four decades or so. Among them we found the following three to be important for our analysis.

First, an increase in business competitiveness and uncertainty lead to a dramatic rise in the idiosyncratic risk of the typical stock (Campbell et al (2001)) mirroring greater firm-specific economic risk4 (Irvine and Pontiff (2009)). Increasingly competitive environment also induced a dramatic augmentation of special items (SPI) because of more frequent asset impairments, restructuring, and gains or losses from asset sales (Donelson et al (2011)).

Second, changes to the fundamental economics of new firms seeking capital gave weaker firms and firms whose expected payoffs are further in the future access to public equity financing. At the origin of the developments in new firms financing, Fama and French (2004) place a change in the supply conditions5 for funding of new lists occurring slowly during the 1980s and 1990s, while Brown and Kapadia (2007) put the increase in financial

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4 Measured by the volatility of cash flows, earnings and sales.
5 Specifically, a downward shift in the supply curve for funding of new list lowers the expected return resulting in positive market values for weaker firms and firms with more distant future payoffs.
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sophistication of the U.S. capital market. As a result, the profitability of the newly listed firms became progressively more left skewed, with large losses more likely, while the growth became progressively more right skewed, with more likely large growth rates. Moreover, there was a sharp increase in the incidence of new unprofitable lists, that is, firms reporting negative earnings.

Third, as the US economy moved towards a knowledge based economy, there was an increase in the intangible capital (innovation, advertising, information technology, human capital, and customer relations). Newer listings are characterized by higher average intangible intensity (Francis and Schipper (1999), Srivastava (2014)).

All three mechanisms of change in the fundamentals of U.S. firms have, possibly, consequences on the EQ measures. For example, firms with more volatile cash flows tend to have more volatile earnings (Lang et al (2006), Barth et al (2008)). Earnings variability is also pushed upwards by increases in special items, a part of earnings that is less persistent the the other components (Fairfield et al (1996), Givoly and Hayn (2000), Jones and Smith (2011)). As the income streams of firms reporting negative earnings are more volatile, a temporal increase in the frequency of net losses should also contribute to a higher earnings volatility.

The rise in earnings volatility should also lower their relevance to prices (Elliott and Hanna, 1996). Moreover, the value relevance of negative earnings is lower than that of positive ones (Collins et al (1997)). An increase in the frequency of loss years should lower the value relevance of earnings.

Since they are less correlated with current revenues than are other expenses, an increase in special items should reduce matching (Donelson et al
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(2011)) while the rising incidence of losses is itself a manifestation of worse matching (Dichev and Tang (2008)).

The immediate expensing of intangible investment should also reduce matching. Moreover, their yearly variations should increase the volatility of earnings as revenues fluctuations do not match those of the intangible investments. In addition, earnings variability of intangible-intensive firms is augmented by the higher uncertainty about future benefits of their investments (Kothari et al (2002)).

2.2 Changes in EQ measures

Contemporaneously, several studies documented sustained lessening of the quality of earnings manifested in a decline in both their relevance (Lev and Zarowin (1999), Collins et al (1997)) and in the matching of concurrent revenues and expenses (Dichev and Tang (2008), Donelson et al (2011)) as well as an increase in their volatility (Givoly and Hayn (2000), Dichev and Tang (2009)). In a seminal contribution, Srivastava (2014) sheds light on the nature of the decline of the EQ by showing that ‘the bulk of the changes in EQ measures over the last 40 years is due to the assimilation of newly listed firms into the firm population and not to changes in the EQ measures of existing firms’ (the new listing phenomenon). In other words, most of the observed decline in the EQ measures reflects changes in the sample of firms.
2.3 Which mechanism of change explains the EQ evolution?

This finding lead to another quandary: Which one among the changing fundamental firm characteristic highlighted by the literature\(^6\) is associated to the decrease in the EQ? Srivastava (2014) asserts that “the biggest factor behind the new-list effect is the widening gap between the intangible intensities of the new- and seasoned-firm segments” (page 198).

In our opinion, the analysis that leads to this conclusion is contentious for several reasons. First, in trying to explain the evolution of the EQ measures, it does not appropriately consider the first two mechanisms of change mentioned above, that is, the increase in the economic riskiness of firms and the drop in their profitability. In particular, the revenue volatility does not capture the increase economic riskiness of firms: in the sample we analyze in the sequel, the correlation between the volatility of cash flows and that of revenues is only 19%. Moreover, as we will see, the evolution of the frequency of reporting SPI does not differ between cohorts and hence this variable is not a good proxy\(^7\) for the first mentioned mechanism of change, that is, increasingly competitive business environment.

Second, the econometric set-up and the statistical tools it uses do not allow for an accurate measuring of the association between the EQ measures and the levels of fundamental firm characteristics competing to explain the decrease of the former. On one hand, the cross-sectional set-up of the analysis yields a small sample of only 40 observations. On the other, the univariate regressions and partial \(R^2\) measures employed are ill suited to control for the effect of other characteristics in estimating associations.

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\(^6\) That is, cash flow volatility, profitability, growth, amount of intangible capital.

\(^7\) The appropriate proxy turns out to be the frequency of loss years.
As a result, the analysis yields biased inferences.

2.4 Aim

The objective of our paper is, hence, to perform a sound, unbiased investigation of the association between the lessening of the EQ measures and the mechanisms of change in the fundamental characteristics of the U.S. firms.

Our approach is closely tailored to address the weaknesses enumerated above. In particular, we emphasize a firm-year approach against a cross-sectional perspective. That is, the EQ measures are constructed for each firm-year observation using firm’s recent history previous to the current year. Since they are not estimated cross-sectionally, we have firm-year idiosyncratic EQ values that can be subjected to a multivariate analysis yielding unbiased estimates of the impact of different characteristics on the EQ measures.

Our analysis shows that changes in firm characteristics associated to the two mechanisms excluded from the analysis in Srivastava (2014), that is, increasingly competitive environment and the changes in the supply conditions for funding of new lists, explain, in a multivariate analysis, the structure of change in the EQ measures.

3 Related literature

3.1 New-listing phenomenon

Brown and Kapadia (2007) introduced the new listing effect in the context of the increase in firm-specific risk in the U.S. stock market. They argue that the increase in idiosyncratic risk (as measured by the idiosyncratic stock
return volatility) is related to more volatile firms being listed through initial public offerings. As a result of increasingly risky firms being listed publicly, the overall composition of publicly traded firms has changed significantly over the last 40 years.

Over time increases (decreases) in a given firm’s characteristic (e.g., risk, intangible intensity, profitability, growth) can take different forms with the two extremes being a pervasive change where the characteristic of most firms in the sample increases (decreases) over time, at one end of the spectrum, and a “new listing effect”-type of change, at the other end. The later evolution is defined by two conditions. First, successive cohorts must display increasing (decreasing) levels of the characteristic. Second, each cohort should evolve, roughly, around its initial level showing no evident trend.

As a result, the increase (decrease) over time in the characteristic of interest is explained mostly by changes in the level of the characteristic between successive listing cohorts. The intra-cohort changes over time are, in this case, less important than the inter-cohort level shifts of the characteristic. Most importantly, the structure specific to the “new listing effect” suggests fundamental changes in the character of the typical publicly traded firm.

Besides arguing that newly listed companies are riskier, Brown and Kapadia (2007) also document that new firms are characterized by progressively riskier fundamentals. Their asset tangibility and profit margins are both diminishing significantly while the values for older firms remain nearly constant. New firms are less likely to pay dividends even as the frequency of dividends among older firms remains constant. Taken together, their evidence suggests that “the expected payoffs of newly listed firms are becoming progressively further in the future and hence, are more difficult to forecast”.

The explanation proposed by Brown and Kapadia (2007) for the “clear and ongoing trend toward riskier firms becoming publicly traded” is the increase in financial sophistication of the U.S. capital market which allowed riskier companies to access capital markets more easily or cheaply. Since the greater idiosyncratic risk of the newer firms is matched by riskier fundamentals, Brown and Kapadia (2007) hypothesize that “the increase in average idiosyncratic risk and the deteriorating fundamentals of publicly traded firms is likely to be related to increasing financial market development”. We review more literature on the evolution of new listings towards riskier fundamentals in the next section.

Srivastava (2014) documents the “new listing effect” in the context of earnings quality. He shows that most of the decline in three EQ measures, that is, earnings volatility, matching and value relevance, over the last 40 years is due to the assimilation of newly listed businesses into the firm population and not to the decline in the EQ measures of existing firms. Towards this end, he decomposed the changes in average EQ measures over the sample period of 1970 to 2009 into “new-list” and “seasoned-firm” effects. The seasoned-firm effect reflects the decline in average EQ measures with no new firms joining the firm sample. The “new listing” effect sums the change in average EQ measures that results from the addition of successive new wave of firms. He finds that the new-list effect contributes as much as 73.9%, 80.0%, and 92.9% to the changes in average relevance, matching, and volatility, respectively, from the period 1970-1974 to the period 2005-2009.

Srivastava (2014) also documents that the increase in firm-specific knowledge intensity over time is of the “new listing” type, i.e. successive cohorts of new firms show increasing intangible intensity and the increases in the knowledge intensity measures over time mainly reflect the increasing mea-
sures of the successive cohorts of new firms rather than increasing knowledge intensity by seasoned firms.

3.2 Intangible intensity explains the decline in EQ measures

Srivastava (2014) argues that, as the United States had moved from being primarily an industrial economy to becoming mainly a knowledge-based economy, there has been a dramatic increase over time in U.S. firms’ average intangible intensity as measured by research and development (R&D) expenses, market-to-book ratios, and selling, general, and administrative (SG&A) expenses.

The analysis uses SG&A intensity as a proxy for intangible intensity because “firms typically expense in-house intangible expenditures through SG&A accounts” and finds that “the biggest factor behind the new-list effect is the widening gap between the intangible intensities of the new- and seasoned-firm segments”. It estimated 12 univariate regressions relating the differences between annual cross-sectional averages of the EQ measures (relevance, matching, or volatility) of the new- and seasoned-firm segments (as dependent variables) with the differences between annual cross-sectional averages of four attributes (as independent variables). The four attributes are: annual difference in special items, revenue volatility, market-to-book ratio, and SG&A intensity.

It reaches its conclusion by comparing the $R^2$ of the individual univariate regressions as well as the partial $R^2$ of 3 multivariate regressions of the differences between annual cross-sectional averages of the EQ measures on the corresponding differences of three of the attributes (annual difference in special items, revenue volatility, and SG&A intensity). Important attributes,
like the frequency of losses or the variability of non-timing-related accruals are not considered. The regressions are estimated on annual cross-sectional differences hence the sample size is small (40 observations). Moreover, the analysis looks only at a very rough partition of the firms between firms with a listing year before 1970 classified as ‘seasoned firms’ and the remaining firms classified as ‘new firms’.

The univariate regressions and the partial $R^2$ measures use to draw the conclusions do not allow for an accurate measuring of the association between the EQ measures and the levels of fundamental firm characteristics as they do not (linear regression) or are ill suited to (partial $R^2$) control for the effect of other characteristics in estimating associations.

3.3 New listings’ riskier fundamentals

The last forty years have brought dramatic changes to the fundamental economics of new firms seeking capital and to the economic environment in which the businesses evolve. These changes were associated with mutations in the fundamentals of typical publicly traded firm. Fama and French (2004) document sharp changes in the profitability and growth of IPOs (with profitability becoming more left skewed and growth more right skewed) associated, most likely, to change in the supply conditions for funding of new lists occurring slowly during the 1980s and 1990s. The increasing dispersion in IPO profitability can be seen in the evolution of the 25th percentile of ROA which falls from 2.7% in 1978 to -21.8% in 1985 and -61.4% in 2001.

Not only the shape of the distribution of profitability changes. Its center lowers through time. For example, “median return on assets (E/A) for 1978 is 11.0%; it declines to 3.6% in 1985, [...] and drops below zero after 1998.
Thus, during 1999-2001 more than half of the IPOs of the last five years are unprofitable.” The sharp increase in the incidence of new unprofitable lists is further emphasized by the following statistics. The percentage of IPO (non-IPO) new lists with negative earnings in their second to fifth year evolves from 14% (11%) 1973-1979, to 41% (38%) 1980-1989, 45% (46%) 1990-2000 and to 72.5% (60%) in 2001.

Moreover, the arrival of numerous new lists with low long-term profitability and high growth eventually causes seasoned firms to acquire similar (if subdued) profitability and growth characteristics, with a corresponding decline in profitability and increase in the frequency of loss years.

Irvine and Pontiff (2009) document “a significant increase over time in the idiosyncratic volatility of firm-level earnings, cash flows, and sales”. They also argue that, over the period 1964-2003, the magnitude of the increase in the idiosyncratic volatility of sales, cash flows, and earnings is large enough to explain the dramatic increase in stock markets idiosyncratic stock-return volatility over the same period (Campbell et al (2001)). They relate the documented increase in the economic and financial firm-level idiosyncratic risk to increasingly competitive environment in which firms have less market power.

Using three variables that serve as proxies for competition: industry turnover (positively associated to competition), return on assets (negatively associated to competition), and the market share of foreign competitors (positive association), they document a trend toward lower ROA (since the late 1980s, the average ROA has been negative, consistent with a trend toward more aggressive competition), higher turnover, and a notable increase in foreign competition. This evidence is consistent with increased competition.
3.4 Changes over time in the revenue-expense relation

Srivastava (2014)’s identification of the widening gap between the intangible intensities of the new- and seasoned-firm segments as the biggest factor behind the decline of the correlation between revenue and expense is at variance with the evidence presented in Donelson et al (2011) which argues that the decline of matching is “primarily attributable to an increase in the incidence of large special items” and relate it to increasing competitive pressure in the economy.

To determine which expense items are responsible for changes in the revenue-expense relation over time, the authors separated total expenses into cost of goods sold, selling, general and administrative expense (SG&A), depreciation, taxes, and special items and showed that the decline in the relation between revenue and current expense is explained primarily by changes to a single income statement line item: special items. Note that SG&A, the variable used in Srivastava (2014) to proxy for the intangibles, is explicitly considered and found not to be associated with the decline in matching.

Next, the authors examined whether increased incidence of special items is due to changes in economic activity or changes in specific accounting standards and found that changes in economic events play a more important role. The economic events associated with recognition of special items considered were: negative employee growth, merger and acquisition activity, discontinued operations, negative revenue growth, and operating losses.

Finally, the authors established a relation between changes in the economic environment and the increasing incidence of special items over time. They construct an index of competitive pressure and find that this index is,
first, increasing and, second, positively associated with the index of economic events related to special item recognition.

3.5 Changes in the landscape of accrual accounting

Our paper is closely related to Bushman et al (2016) which investigate a temporal change in a fourth EQ measure, the correlation between accruals and cash flows, over the past decades. It shows that “the correlation between accruals and cash flows has dramatically diminished in magnitude over the past half century and has largely disappeared in more recent years”. Having documented correlation’s decline, the paper looks at various fundamental characteristics of firms whose changes might have been associated with the evolution of this EQ measure: economic-based cash flow shocks (as measured by the cash flow volatility), timing-based cash flow shocks (as measured by the first order auto-correlation of changes in CFO), size of one-time items, size of non-operating items, loss years, matching of revenues and expenses, and intangible intensity (as measured by SG&A intensity). It concludes that one-time and non-operating items and loss firms are mostly responsible for the attenuation in the overall correlation between accruals and cash flows. Most importantly, based on a multiple regression analysis, the authors find that the effect of temporal changes in intangible intensity is not significant (being subsumed by other explanatory variables).

Our analysis agrees with the results summarized above. It finds that changes in the frequency of loss years are mostly responsible for the decline in three measures of EQ which are at the center of Srivastava (2014), while the effect of temporal changes in intangible intensity is not significant
being subsumed by other explanatory variables, like, profitability, economic riskiness or growth.

To summarize, previous literature documents important changes in the fundamentals of new listings over the last forty years with the arrival to the market of less profitable (left skewed profitability, higher incidence of negative earnings), riskier (higher probability of delisting for poor performance, more volatile cash flow streams) and more intangible intensive firms. These developments are associated with changes to the fundamental economics of new firms seeking capital and to the economic environment in which the businesses evolved characterized by increased competition and by a trend towards a knowledge and services economy.

This review of the relevant literature helps also identify fundamental firm characteristics (as well as their proxies) that have changed over the last few decades and that might be associated with the decline of the EQ measures. These are: intangible intensity proxied by $SG&A$ intensity, profitability, measures by the return on assets (ROA) and the frequency of loss years, growth, as expressed by the growth of total assets (TA), economic riskiness measured by the amplitude of the economic-based shocks to the cash flow, and the variability of non-timing-related accruals measured by the volatility of special items (SPI) or SPI plus non-operating items (NOPI). These characteristics and their proxies will be the focus of the empirical analysis in section 6.

\footnote{Following Srivastava (2014) we use $SG&A$ intensity as a proxy for intangible intensity because firms typically expense in-house intangible expenditures through $SG&A$ accounts (Banker et al (2011), Eisfeldt and Papanikolaou (2013)).}
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4 Methodological aspects

As mentioned in the introduction, the earnings relevance, one of the three EQ measures in Srivastava (2014), defined as the adjusted-$R^2$ of the regression of annual stock returns on the levels of, and changes in, annual earnings, is not suited for a conditional analysis. While the value relevance measure assigns the same value to all firms in a cross-section, a conditional analysis needs firm-specific measures of the level of association of earnings with prices. Moreover, the returns earnings regression is an empirical specifications of a representation\(^9\) of the RI model that is not necessary a regression. As such, it is not guaranteed to truthfully infer the economic relation in the RI valuation (Kang and Starica (2016)). To address these two issues, we employ the expectation formation pertinence (EFP) research design of Kang and Starica (2016) which we briefly resume in the next section. For more details, see the Appendix as well as the cited reference.

4.1 An alternative to the earnings relevance quality measure

Research that examines the association between accounting amounts and equity market values requires a research design composed of three elements: first, a valuation model to designate the firm attributes that affect value and their relation to value, second, a practical stipulation of the model for empirical tests, and, third, a measure of association.

\(^9\) We are referring here to the Ohlson model (Ohlson (1995)).
4.1.1 Value relevance research design

Holthausen and Watts (2001) give a synthesis of the modus operandi of a relative association study conducted in the value relevance framework: “Relative association studies compare the association between stock market values (or changes in values) and alternative bottom-line measures [...]. These studies usually test for differences in the $R^2$ of regressions using different bottom line accounting numbers. The accounting number with the greater $R^2$ is described as being more value-relevant.” A quarter of the 62 papers under discussion in Holthausen and Watts (2001) perform a relative association study.

A frequently employed specification of the research design triad in such studies consists of Ohlson’s linear solution to the RI equation$^{10}$ (the valuation model), price-levels or returns-earnings regressions estimated on cross-sectional data (empirical stipulations of the model), and regression’s $R^2$ (the measure of association).

Extant literature has highlighted issues concerning each one of the three elements of the mentioned research design. The shortcomings of the Ohlson specification are tied to the linear assumptions on the dynamic of the residual earnings (Holthausen and Watts (2001)). The estimation of price-levels and returns-earnings regressions is potentially impaired by bias due, on one hand, to error terms correlated with the independent variables (Lo (2005), Barth and Clinch (2009)) and, on another hand, to coefficients that are functions of firm-specific risk characteristics and industry-specific dynamic of the residual earnings (Kothari and Shanken (2003)), and hence not cross-sectionally

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$^{10}$ More generally, twenty-nine of the sixty two studies, that is 47% of the studies, under discussion in Holthausen and Watts (2001) base the specification of their empirical tests on the Ohlson model.
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constant\textsuperscript{11}. Finally, the use of regression’s explanatory power as an association measure is controversial due to the fact that $R^2$ is a combination of parameters relevant to the economic relation being inferred (the variance of the error term) and of parameters of the population (the variability of the dependent variable in the sample) (Gu (2007)). This mixture makes it difficult to trace whether a change in the explanatory power is due to differences in the economic relation or to differences between samples.

\[ P_{i,t} = B_{i,t} + \sum_{u=1}^{\infty} \frac{\mathbb{E}_t[NI_{i,t+u} - r_{i,t} \times B_{i,t+u-1}]}{(1 + r_{i,t})^u} = B_{i,t} + \sum_{u=1}^{\infty} \mathbb{E}_t[RI_{i,t+u}] \frac{1}{(1 + r_{i,t})^u}, \]  

(1)

\[ (r_t \text{ denotes the price of equity risk at time } t \text{ while } \mathbb{E}_t \text{ stands for market’s expectation conditional on all information available at time } t). \]

\textsuperscript{11} One can prove that these two causes of inconsistency are \textit{structural} and hence not easily avoidable in an empirical setting. In particular, Ohlson’s linear expression of the relation between value and accounting numbers, the \textit{raison d’être} of the two specifications, is not itself a regression. Consequently, its two empirical specifications are \textit{by definition} ill-suited for consistent estimation.
tive assumptions are made on how observed values project future abnormal earnings.

2. Empirical specification (motivated by the results\textsuperscript{12} in Kang and Starica (2016))

For any given set of predictors $\text{PREDICT.RI}$ of future residual earnings, the economic relation postulated by the RI model (1) can be expressed in the form of a (non-linear) regression in which the price is the dependent variable and the set of predictors $\text{PREDICT.RI}$ form the independent variables (see definition 1 in the Appendices). In other words, the price can be decomposed as a sum between a (non-linear) function $m$ of the predictors $\text{PREDICT.RI}$ and an error term $\varepsilon$ which is orthogonal on the predictors set. The orthogonality property guarantees that the function $m$ can be consistently inferred using proven techniques from the non-parametric regression literature.

More precisely, for a generic firm $i$, belonging to industry $I$, of size $S_i$, characterized by an conservative accounting level $C_i$, and for a given set of RI predictors $\text{PREDICT.RI}$, at moment $t$, there exists a possibly non-linear, industry- and predictor-specific function and an error term $\varepsilon_i$ such that:

$$P_{i,t} - B_{i,t} := m_{I,t}(\text{PREDICT.RI}_{i,t}; r_{i,t}, S_{i,t}, C_{i,t}) + \varepsilon_{i,t}, \quad (2)$$

where the error term satisfies the orthogonality condition

$$E_t[\varepsilon_i | \text{PREDICT.RI}_i] = 0.$$

According to Kang and Starica (2016), the representation in (2) can be interpreted as a decomposition of the market price into a valuation incorpo-

\textsuperscript{12} The relevant results in Kang and Starica (2016) are briefly recalled in the Appendices.
rating expectations of future abnormal earnings formed only on the basis of the accounting variables of interest PREDICT.RI (represented by the regression function $m$ evaluated at the set of predictors PREDICT.RI) and an investors’ adjustment to this valuation based on other (than the level of the variables in PREDICT.RI) information available (represented by $\varepsilon$, the error term of the regression).

The specifications (2) are regressions (in the sense of definition 1 in the Appendices). Therefore, the functions $m$ can be consistently estimated on cross-sections of firms in the same industry (and cohort) by employing proven inference techniques from the field of non-parametric regression (see corollary 1 in the Appendices). Their estimates, $\hat{m}$, are theoretically guaranteed to be unbiased.

3. Firm-specific measure of association (derived from an accounting perspective)

According to the previous interpretation (see also proposition 1 in the Appendices), the size of the pricing error

$$|\hat{\varepsilon}_{i,t}| = |P_{i,t} - B_{i,t} - \hat{m}_{I,t}|$$

quantifies the extent to which future earnings expectations are shaped by information other than the predictor set PREDICT.RI.

For a given pair $(i, t)$, we define the absolute relative valuation error to be the firm-year-specific measure of association (expectation formation pertinence) for the data entry $(i, t)$:

$$EFP_{i,t} := \frac{|\hat{\varepsilon}_{i,t}|}{P_{i,t}} = \left| \frac{P_{i,t} - B_{i,t} - \hat{m}_{I,t}}{P_{i,t}} \right| .$$

(3)
It amounts to the proportion of the price corresponding to earnings expectations shaped by information other than the current values of the set of predictors.

This research design is particularly useful when investigating if a predictors association with prices depends on a given firm’s characteristic. An example of such a research question would be: Are earnings of firms in earlier cohorts more relevant to investors price setting than those of firms listed later? In the outlined expectation formation pertinence framework, the researcher would split the sample conditional on the level of firms characteristic (in the case of the example into competing subsets of earlier-listed and more recently-listed firms) and test for differences in the median size of the absolute pricing error calculated on the sub-samples. She would interpret statistically significant differences as evidence of the impact of the given firms characteristic on the predictors pertinence to the expectation formation. In our example, if firms in earlier cohorts command higher valuation accuracy than firms in later waves, we would answer the research question positively.

4.1.3 Estimation of the non-linear valuation regressions

The non-linear regression relations specified by (2) can be consistently estimated using techniques from the field of non-parametric statistics. We considered and compared a number of conceptually different estimation approaches: Additive Model (AM), Projection Pursuit Regression (PPR), Classification and Regression Trees (CART), Multivariate Adaptive Regression Splines (MARS). Our robustness analysis shows that the results presented in the paper are robust to the choice of the estimation method.
Linear regression is a global model assuming a single predictive formula that holds over the entire data-space. It also falls into the category of so-called *parametric regressions*, which assumes the relationships (but not the specific parameters) between the dependent and independent variables to be known *a priori* (in our case this relation is linear). (By contrast, non-parametric regression does not make any such assumption allowing instead the regression function to be "driven" directly by the data.)

When the independent variables interact in complex, non-linear ways, putting in place a parametric model can be difficult. Two conceptually distinct solutions to this issue can be considered. The first is to fit a global nonlinear regression form of the way the independent variables are associated to the independent one.

The AM and PPR methods belong to this approach. Both fit a linear combination of smooth, univariate, non-parametric functions. The 'non-parametric' term means that the shape of the regression functions are determined by the data as opposed to 'parametric' functions that are defined by a typically small set of parameters. This will allow for more flexible estimation of the underlying regression patterns without knowing upfront what these patterns might look like. The AM considers sums of functions taking arguments in the natural coordinates of the space of explanatory variables while PPR handles the case when the underlying function is additive with respect to variables formed by linear combinations of the original explanatory variables.

The second alternative is to partition the independent variable space into smaller regions where the relation between the regressors and the regressed is more manageable and to fit on each region a simple linear models. The main
ingredient of such an approach is the recursive partitioning of the variables space to regions small enough to display a simple structure to which we can fit simple models. This alternative approach to linear regression yields the class of recursive partitioning regression models.

MARS and CART belong to this class of models. They are non-parametric approaches that build flexible models by fitting piece-wise linear models on regions of the space of independent variables. CART fits local constants while MARS fits piece-wise linear regressions. In a comparison with the simpler one-dimensional set-up, MARS generalizes the piece-wise linear regression, where each break-point (estimated from the data) defines the "region of application" for a particular (very simple) linear regression equation.

More details about the three techniques can be found in section B of the Appendices. See also James et al (2014)) and Wasserman (2006).

4.2 Second step: The association between firms characteristics and EQ

This section deals with the methodological challenges of the second step of our approach, that is, the investigation of the relation between EQ measures and firm characteristics. Since our goal is to disentangle the individual association of firm characteristics, such as intangible intensity, profitability, size or cash flow volatility, to earnings quality measures, a natural tool to use is the multiple regression which allows us to quantify the impact of a firm characteristic while holding the level of the other constant. However, there is no reason to assume a linear relation between the level of the quality constructs and firm characteristics. Contrary, it is very plausible that the change in the association with EQ corresponding to an incremental change in the value of a firm characteristic will depend on the level of firm’s characteristic.
As a consequence, the use of the plain vanilla linear regression might not be suitable.

Our atypical use of the linear regression exploits its versatility avoiding the assumption of linearity in the relation between the regressor and the independent variables. More precisely, our analysis uses the linear regression as a tool for testing differences in mean. This section gives the details of this less common usage.

It is well known that, when the independent variable in a linear regression is an indicator variable, testing the null hypothesis of zero regression coefficient is equivalent to testing that the means of the dependent variable conditional on the presence or absence of the character modeled by the binary variable are equal (see, e.g., Stock and Watson (2012)). In particular, if the indicator variable models contrasting values of a given character (e.g. high vs. low) a significant non-zero regression coefficient of the binary variable indicates statistically distinct means of the independent variable conditional on the level of the character that is modeled by the indicator variables.

More generally, if the range of values of the character is split in \( l + 1 \) intervals of equal probability\(^{13} \), \( (a_{\min}, a_1], (a_1, a_2], \ldots, (a_{l-1}, a_l], (a_l, a_{\max}) \), \( l \) indicator functions denoted \( D^{(Ch,k)} \), \( k \in \{1, 2, \ldots, l\} \), modeling the different levels of the character \( Ch \), will form the independent variable set while one level (in this case, the smaller values of the character) will be the reference.

Formally, if we denote by \( Y \) the independent variable and by \( Ch \) the firm characteristic that explains it, our approach replaces the classical linear regression

\[
Y_i = \gamma_0 + \gamma \ Ch_i + \epsilon_i
\]

\(^{13} \) In this case \( a_i \) is the \( i/(l+1) \)-quantile.
by the following:

\[ Y_i = \gamma_0 + \gamma_1 D_i^{(Ch,1)} + \gamma_2 D_i^{(Ch,2)} + \ldots + \gamma_l D_i^{(Ch,l)} + \epsilon_i, \tag{4} \]

where \( D^{(Ch,k)} \) denotes the indicator function of the \( k \)-th level of firm’s characteristic \( Ch \) as described above.

In this set-up, a significant non-zero regression coefficient of the \( k \)-th indicator variable \( \gamma_k \) means that the mean of the independent variable \( Y \) conditional on the character \( Ch \) taking values in the \( k \)-th bracket of its range, \((a_{k-1}, a_k]\), is statistically different from \( Y \)’s mean value when conditioning with the character’s reference values, \((a_{\min}, a_1]\). Significant non-zero coefficients are evidence of association between the variable \( Y \) (in our case, an EQ measure) and firm’s characteristic \( Ch \).

To simplify notation we will use

\[ Y_i = \gamma_0 + \gamma \times D_i^{(Ch)} + \epsilon_i \tag{5} \]

to denote the regression in (4).

This particular set-up of the linear regression allows us to take advantage of linear regression’s versatility without imposing an assumption of linearity on the relationship between the variables. We can, first of all, control for factors that are known to affect the relation between pricing accuracy and different earnings quality constructs (like size, sign of the earnings, intangible intensity) and, second, estimate un-biased coefficients reflecting the true impact of a given constructs on the pricing accuracy of the valuation regression by including among the regressors other constructs which, when omitted, cause estimation bias.
4.3 Third step: EQ over time

To statistically evaluate the impact of cohort membership as well as that of changes in firm’s characteristics on the EQ measures, we compare the distributions of the later conditional, first, on the cohort and, second, on the cohort and on the level of firm characteristics. Significant dissimilarities in measures of the conditional distributions, such as the conditional mean, would indicate significant dependence of the EQ measures upon cohort and upon changes in the characteristics of the firm.

The probabilistic constructs we examine in the sequel are the yearly mean EQ measure conditional on belonging to cohort Co:

\[ \mathbb{E}[EQ_t | Co], \]  

(6)

and the yearly mean EQ measure conditional on belonging to cohort Co and conditional on the level of firm characteristics Ch at time t:

\[ \mathbb{E}[EQ_t | Co, Ch_t], \]  

(7)

\((t \text{ stands for the current year}).\)

4.3.1 The moving-window multiple regression set-up

To infer \( \mathbb{E}[EQ_t | Co] \), the mean EQ at time t measure conditional on belonging to cohort Co in (6), we estimate the following unbalanced time-fixed effect panel linear model on a 3-year moving window centered at year t:

\[ EQ_{i,u} = \mu(t) + \beta_1(t)D_{i,u}^{(Co_1)} + \beta_2(t)D_{i,u}^{(Co_2)} + \ldots + \beta_m(t)D_{i,u}^{(Co_m)} , \]  

(8)
where \( u \in \{ t - 1, t, t + 1 \} \), \( D^{(Co_j)} \) stands for the dummy variable corresponding to membership in cohort \( j \). There are \( m + 1 \) cohorts at year \( t \), \( Co_0, Co_1, \ldots, Co_m \) and cohort 0 is taken as reference.

To estimate \( \mathbb{E}[EQ_t | Co, Ch_t] \), the mean EQ measure conditional on belonging to cohort \( Co \) and conditional on the level of firm characteristics \( Ch \) at time \( t \) in (7), we add to the explanatory variables in (8) the level indicators of the characteristic \( Ch \) we want to control for, yielding the following regression:

\[
EQ_{i,u} = \mu(t) + \beta_1(t)D_{i,u}^{(Co_1)} + \beta_2(t)D_{i,u}^{(Co_2)} + \ldots + \beta_m(t)D_{i,u}^{(Co_m)} + \gamma_1(t)D_{i,u}^{(Ch,1)} + \gamma_2(t)D_{i,u}^{(Ch,2)} + \ldots + \gamma_l(t)D_{i,u}^{(Ch,l)} + \epsilon_{i,u}, \tag{9}
\]

where \( D^{(Ch,k)} \) denotes the indicator function of the \( k \)-th level of firm’s characteristic \( Ch \) as introduced in section 4.2.

Using the shorthand notation in (5), the regressions (8) and (9) become:

\[
EQ_{i,u} = \mu(t) + \beta(t) \times D_{i,u}^{(Co)} + \epsilon_{i,t}
\]

\[
EQ_{i,u} = \mu(t) + \beta(t) \times D_{i,u}^{(Co)} + \gamma(t) \times D_{i,u}^{(Ch)} + \epsilon_{i,t},
\]

where \( u \in \{ t - 1, t, t + 1 \} \).

The regression in (8) supposes that the distribution of earnings qualities changes through time. To capture this time evolution we perform the regression on a window that moves through the sample. Window sizes different from the choice presented, i.e., width of two or three, yield qualitatively identical results.
The parameters in (9) have intuitive interpretations:

\[
\mu(t) = \mathbb{E}[EQ_t \mid Co_0, D^{Ch,0}],
\]
\[
\beta_j(t) = \mathbb{E}[EQ_t \mid Co_j, Ch_t] - \mathbb{E}[EQ_t \mid Co_0, Ch_t], \quad j \in \{1, 2, \ldots, m\}.
\]

In words, \(\mu(t)\) is the mean \(EQ\) of the reference cohort in year \(t\) when the characteristic \(Ch_t\) belongs to the reference interval, while \(\beta_j(t)\) is the incremental change in mean \(EQ\) of firms belonging to cohort \(j\) over the mean \(EQ\) in the reference cohort during the year \(t\) holding the level of the firm characteristic \(Ch\) constant. Coefficients \(\beta_j(t)\) strictly greater (smaller) than 0 provide evidence of lower (higher) mean \(EQ\) for firms in cohort \(j\) with respect to reference cohort (in the year \(t\)) when holding the level of the firm characteristic \(Ch\) constant.

4.3.2 Statistical hypothesis testing set-up

In the analysis to follow, the reference cohort will be that of the seasoned firms, that is, the firms that were listed before 1970 (and have the historical information needed for the inference of the \(EQ\) measures). Formally, for a given year \(t\), we perform the following hypothesis test:

\[
H_0 : \quad \beta_j(t) = 0
\]
\[
\text{vs.}
\]
\[
H_1 : \quad \beta_j(t) > 0 \quad (\beta_j(t) > 0),
\]

with \(j \in \{1, 2, \ldots, m\}\).

The test is performed by constructing a 95% one-sided confidence interval for the coefficient \(\beta_j(t)\) that we display around \(\beta_j(t)\) and verifying if 0 belongs
to it. If it does, the null is not rejected. If it does not (and the estimated coefficient is strictly positive/negative), that is,

$$\mathbb{E}[EQ_t | Co_j, Ch_t] > (<) \mathbb{E}[EQ_t | Co_0, Ch_t],$$

we conclude that the average EQ measure in the later cohort $j$ is higher (lower) than that for the seasoned firms holding the level of firm’s characteristic $Ch$ constant.

As the year $t$ moves through the sample, the estimation of the regression (8) yields $m$ curves, that is, $\beta_j(t), j = 1, 2, \ldots, m$ which follow the time evolution of the incremental increase/decrease of the EQ measure for firms in cohort $j$ relative to the reference cohort of seasoned firms. The results of the empirical analysis in section 6 will be presented in the form of graphs displaying these $m$ curves together with the $m$ one-sided 95% confidence intervals for hypothesis testing.

5 Variables, sample, and cohort construction

Deliberately following Srivastava (2014) we define accruals (TACC) as change in Current Assets ($ACT$) minus change in Cash ($CHE$) minus change in Current Liabilities ($LCT$) minus change in Tax Payable ($TXP$) minus Depreciation and Amortization ($DP$), scaled by average Total Assets (Compustat $AT$) for the year. Cash flow from operations is defined as the difference between earnings (Compustat $IB$) and accruals.
5.1 Key variable definitions

5.1.1 SG&A intensity

Following Dichev and Tang (2008) and Srivastava (2014), we compute total expenses by subtracting income before extraordinary items (Compustat IB) from revenues (Compustat SALES). We measure the SG&A expenses by the Compustat data item XSGA, and define the SG&A intensity as the proportion the SG&A expenses represent in the firm-year’s total expenses, that is, as the ratio between XSGA and total expenses.

5.1.2 Earnings and cash flow volatility

Following Givoly and Hayn (2000) and Dichev and Tang (2009) we scale earnings and cash flows from operations by the average of the beginning and ending of the year total assets and estimate the standard deviations of these variables for each firm-year using eight annual observations ($t−7$ through $t$).

We emphasize here our choice of a rather long window of past observations for the estimation of the two volatilities, in line with that in Dichev and Tang (2008) but contrasting the choice of Srivastava (2014). We did not feel (statistically) comfortable replicating the short window length of “previous two years, the current year, and the next year” in the later reference. Such a choice implies estimating two parameters, that is, the first two moments of earnings or cash flows, with four observations. To put it differently, each moment is estimated using two observations. Making statistically sound statements based on parameters estimated on samples of size two seemed to us difficult, if not impossible.
However, a cleaner statistical conscience comes at a cost: the constraint of availability of relevant accounting items for a longer spell of previous years drastically reduces the sample size as visible in the sample description in section 5.2. Facing a choice between making sensible statements based on sound statistics derived from a sample biased towards firms that survived their first 7 years on the exchange, on one hand, and a possibly misleading statistical analysis performed on a more exhaustive sample (nevertheless biased towards firms that survived their first 4 years) on the other, we preferred the former.

### 5.1.3 Matching

Following Dichev and Tang (2008), we measure matching by the correlation between contemporaneous revenues and total expenses scaled by the average of the beginning and ending of the year total assets, \( \text{cor}(\text{Revenues}, \text{Expenses}) \), estimated for each firm-year \((i, t)\) on the sample of eight annual observations \((t - 7 \text{ through } t)\).

Although yielding identical results (albeit with significantly wider confidence intervals), we prefer this definition to estimating the matching regression at firm-year \((i, t)\):

\[
\text{Revenues}_{i,u} = b_{1,i}(t) + b_{2,i}(t) \text{ Total Expenses}_{i,u-1} + b_{3,i}(t) \text{ Total Expenses}_{i,u} + b_{4,i}(t) \text{ Total Expenses}_{i,u+1} + \epsilon_{i,u},
\]

on the 6 triplets \((t, t-1, t-2), (t-1, t-2, t-3), \ldots, (t-5, t-6, t-7)\) and measuring matching by the regression coefficient on the contemporaneous expenses \(b_{3,i}(t)\). The reason is the poor ratio number of data points to number of parameters to estimate, the same statistical concern we discussed.
Changes in earnings quality: a competing narrative

in the previous section. The regression definition of matching would estimate 4 parameters with 6 data points.

5.1.4 Earnings expectation formation pertinence

To construct the firm-year measure of pertinence we first consistently estimate\(^{14}\) the regression in (2) for each industry \(I\), cohort \(Co\) and year \(t\) in the sample. Denoting by \(\hat{m}_{I,Co}\) the estimated regression function, the inference yields a valuation of each of the firms in the sample at time \(t\):

\[
\hat{P}_{i,t} := B_{i,t} + \hat{m}_{I,Co}(NI_{i,t} ; r_{i,t}, S_{i,t}, C_{i,t}), \quad i \in I \cap Co,
\]

and, hence, an year- and firm-specific estimated relative valuation error:

\[
\frac{\varepsilon}{P_{i,t}} = \frac{P_{i,t} - \hat{P}_{i,t}}{P_{i,t}}.
\]

For details on the estimation of the regression in (2), see section B in the Appendices.

The absolute value of the relative valuation error above is our measure of the expectation formation pertinence of earnings.

5.1.5 Fundamental firm characteristics

The firm characteristics that explain the EQ measures differences between cohorts are defined as follows. Frequency of loss years (\(\%NI < 0\)) and frequency of negative special items (\(\%SPI < 0\)) are measured by the number of years in the recent 8 year history the firm reported negative earnings, negative

\(^{14}\) To make sure that all pairs (industry, cohort) have enough observations for a consistent inference, the estimation is performed on a 5 year moving window \(\{t - 4, t - 3, \ldots, t\}\).
special items (Compustat SPI), respectively. Median accounting profitability (median(ROA)) and median total assets growth rate (AT growth) are constructed as the median value of return on assets and total assets growth, respectively, over the most recent 8 years. The yearly total assets growth rate is calculated as the change in total assets (Compustat AT) divided by previous year’s total assets.

5.2 Sample

The initial sample, obtained from Compustat (accounting information) and CRSP (prices) data bases, covers the 53-year period between 1963 and 2015. Starting from it, we created two samples, one for constructing the expectation formation pertinence measure and the other for generating the other EQ measures as well as the explaining firm characteristics.

The expectation formation pertinence sample includes all the firms-years for which the values of the variables needed for running the \( P - B \) regression (2) were available. This sample consists of 182,345 firm-year observations with the number of firms meeting the requirements ranging from 698 to 6,116 per year, with an yearly average of 3,517 firms. This sample contains 16,686 distinct firms. The non-linear valuation regression is estimated\(^{15}\) on sub-samples defined by the intersection of year, industry (SIC 2) and cohort by means of the non-parametric approaches detailed in section B in the Appendices. The results reported in the paper were obtained using the Projection Pursuit (PPR) estimation approach. We then construct the absolute values of the relative pricing errors, our measure of expectation formation pertinence.

\(^{15}\) For the sake of consistency, we require a sample size of the cross-sectional industry-cohort sub-sample not smaller than 30.
The other two EQ measures, that is, earnings volatility and matching, and a number of fundamental characteristics are also firm- and year-specific and are computed on the recent history of each firm (see the section 5.1 for details). We designed the second sample to contain the necessary information for their construction. More precisely, the second sample contains all the firm-years for which the previous seven year history including earnings, cash flows from operations, revenues, expenses, total assets, and reported SPI, is available.

The final sample is obtained as the intersection of the expectation formation pertinence sample and the EQ measures sample. It contains all the firms in the original sample for which we were able to construct the expectation formation measures and the EQ quality proxies together with the fundamental firm characteristics. It covers the period from 1971 to 2015 and contains 86,187 firm-year observations. Figure 1 shows that the number of firms meeting the requirements ranges from 241 to 2,676 per year, with an average of

\[ \text{average number of firms per year} \]

The final sample coincides practically with the smaller EQ measures sample.
1,912 firms per year. In total, the sample contains 8,279 distinct firms. The EQ measures are winsorized at the 1% level to control for outliers.

Table 1 displays the summary statistics of the variables needed to estimate the regression (2) (Panel A), of the variables used to construct the EQ measures (Panel B) and of the EQ measures and the explanatory firm characteristics (Panel C).

Table 2 displays the values of Spearman (upper triangle) and Pearson (lower triangle) correlation between regression variables (EQ measures and explanatory firm characteristics).

5.3 Cohort definition

We classify the firms in the sample in five cohorts. The reference cohort $Co_0, (j = 0)$ is formed by the firms that entered the data base before 1970. The other cohorts initiate at regular ten year intervals and contain the firms that are listed during the 10 years after the starting year. This yields four more cohorts, that is, $Co_1 = 1970 – 1979 (j = 1), Co_2 = 1980 – 1989 (j = 2), Co_3 = 1990 – 1999 (j = 3)$, and $Co_4 = 2000 – 2009 (j = 4)$. We start following the cohorts 10 years after their inception. That gives us 46 years of follow-up for the reference cohort, 36 years for the first cohort, 26 for the second, 16 years for the third, and 6 years for the fourth.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
<th>10%</th>
<th>25%</th>
<th>50%</th>
<th>75%</th>
<th>90%</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Variables for the non-linear pricing regression</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>$P_0/B_0$</td>
<td>8.01</td>
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<tr>
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<td>0.00</td>
<td>0.01</td>
<td>0.02</td>
<td>0.03</td>
</tr>
<tr>
<td><strong>Panel C: EQ measures and explanatory characteristics</strong></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>$\sigma(NI)$</td>
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<td>0.08</td>
<td>0.01</td>
<td>0.02</td>
<td>0.04</td>
<td>0.08</td>
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<tr>
<td>$\text{corr}(Rev,Exp)$</td>
<td>0.91</td>
<td>0.17</td>
<td>0.74</td>
<td>0.91</td>
<td>0.98</td>
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<tr>
<td>$EFP$</td>
<td>0.44</td>
<td>0.59</td>
<td>0.05</td>
<td>0.12</td>
<td>0.26</td>
<td>0.49</td>
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<tr>
<td>$SG&amp;A\text{intensity}$</td>
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<td>0.16</td>
<td>0.07</td>
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<td>0.21</td>
<td>0.33</td>
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<tr>
<td>$%NI &lt; 0$</td>
<td>0.35</td>
<td>0.22</td>
<td>0.12</td>
<td>0.12</td>
<td>0.25</td>
<td>0.50</td>
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<tr>
<td>$\text{median}(ROA)$</td>
<td>0.02</td>
<td>0.13</td>
<td>-0.09</td>
<td>0.01</td>
<td>0.04</td>
<td>0.08</td>
<td>0.12</td>
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<tr>
<td>$\text{median}(AT growth)$</td>
<td>0.08</td>
<td>0.10</td>
<td>-0.04</td>
<td>0.01</td>
<td>0.07</td>
<td>0.13</td>
<td>0.20</td>
</tr>
<tr>
<td>$\sigma(CFO)$</td>
<td>0.09</td>
<td>0.08</td>
<td>0.03</td>
<td>0.04</td>
<td>0.07</td>
<td>0.11</td>
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<tr>
<td>$%SPI &lt; 0$</td>
<td>0.38</td>
<td>0.22</td>
<td>0.12</td>
<td>0.12</td>
<td>0.38</td>
<td>0.50</td>
<td>0.75</td>
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<tr>
<td>$\sigma(SPI)$</td>
<td>0.04</td>
<td>0.05</td>
<td>0.00</td>
<td>0.01</td>
<td>0.02</td>
<td>0.04</td>
<td>0.09</td>
</tr>
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Table 1: **Descriptive statistics.** Panel A: variables for constructing the expectation formation pertinence measure, Panel B: variables used to calculate the EQ measures, Panel C: EQ measures and explaining fundamental firm characteristics.
Table 2: Correlation between regression variables (EQ measures and explanatory characteristics). Lower triangle: Pearson correlation, Upper triangle: Spearman correlation. The vertical/horizontal lines separate the dependent variables from the independent ones.

6 Empirical results

6.1 Patterns of change in the EQ measures and fundamental characteristics

This section investigates the time evolution of the EQ measures and that of fundamental firm characteristics possibly associated to the former. We document, for the majority of them, a “listing effect” type of evolution. Towards this end, we calculate and display the mean value of the attribute under study conditional on the cohort and year. The conditional mean is calculated on a moving window of size 5. This results in five curves describing the change over time of the cohort-specific average attribute. Figures 2, 3 and 4 display the results for the three EQ measures, for the four fundamental firm characteristics that show a clear pattern of listing effect, and for three others that display a different dynamic of change, respectively.
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Fig. 2: Time evolution of the EQ measures. The plots display cohorts’ mean of the three EQ measures estimated on a 5 year moving window. Earnings volatility (top-left), the $\text{corr(Rev, Exp)}$ (top-right), and $EFP$, the absolute value of the relative error of the pricing regression (2) (on a logarithmic scale) (bottom). All three measures show evidence of the “listing effect”.

Figures 2 and 3 show that successive cohorts display increasing levels of earnings and cash flow volatility, expectation formation pertinence, $SG&A$ intensity, and number of loss years in the 8 year recent history of the firm, and decreasing levels for matching and accounting profitability, respectively. Moreover, the cohorts evolve, roughly, around their initial level showing little evidence of a common trend. The variation of the expectation formation pertinence are more pronounced with evident swings around the internet bubble and the 2008 financial crisis. Nevertheless and despite these variations, the cohort evolution does not display an evident increase (if anything, the cohort trend might point slightly downwards).
As a result, the increase (decrease) over time in the characteristic of interest is explained mostly by changes in the level of the characteristic in successive listing cohorts.

![Graphs showing time evolution of relevant firm's characteristics.](image)

**Fig. 3:** Time evolution of relevant firm’s characteristics. The plots display cohorts’ mean firm’s characteristic value estimated on a 5 year moving window: SG&A intensity (top-left), number of loss years in the recent 8 year history of the firm (top-right), ROA (bottom-left), and CFO volatility (bottom-right). All three measures show evidence of the “listing effect”.

Figure 4 shows the existence of other patterns of conditional change (than the ’listing effect’). The size and the TA growth show a net separation between cohorts, the first condition of a listing effect. However, the cohort dynamic display a clear common trend, upward for the size and downward for the TA growth, with the trend for size being clearer. Hence the second condition of a listing effect is not fulfilled. The evolution of the population of
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firms comes from a generalized increase/decrease in the values of the characteristic, albeit at possibly cohort-specific speed.

Fig. 4: Time evolution of relevant firm’s characteristics. The plots display cohorts’ mean firm’s characteristic value estimated on a 5 year moving window: log(TA) (top-left), TA growth (top-right), SPI volatility (bottom-left), number of negative reported SPI in the recent 8 year history of the firm (bottom-right).

The third graph, the time evolution of SPI volatility, displays a mixture of patterns. While the first two cohorts follow an identical evolution consisting in a progressive increase, the more recent cohorts display shifts in the level as well as a downwards trend in the more recent years.

The last graph in Figure 4 documents a steady increase in the mean frequency of reporting (negative) SPI with the cohorts being difficult to separate. Since the time evolution of this firm characteristic is common to the four cohorts, it cannot explain the inter-cohort differences documented in
Figure 2. For this reason we will use the frequency of negative *earnings before special items* (or *persistent earnings*) in the multivariate regressions in the second and third step of our analysis.

6.2 Firm characteristics associated with the EQ measures

The analysis in this section has several goals. First, it aims at estimating consistently the association between EQ measures and the proxy for intangible intensity. We will show that, although it seems significantly negative in a regression on only the levels of SG&A intensity, this association is greatly reduced once we control for the level of some of the characteristics discussed in the previous section. The large coefficients in the simple regression are due to the omitted variable bias.

Second, we establish which of the firm characteristics in section are significantly associated with each of the EQ measures. This step will help us determine (in the next section) the fundamental firm characteristics whose dynamic is associated with the changes in the EQ measures.

To attain these goals, we ran two regressions for each EQ measure which differ through the set of the independent variables. The first set contains only the level indicators of the SG&A intensity:

\[
EQ_i = \gamma_0 + \gamma^{(u)} \times D_i^{(SGA)} + \epsilon_i
\]  

(11)

The estimated coefficients \(\gamma^{(u)}\) (uncontrolled) reflect the association without controlling for possible bias due to omitted characteristics. The second set adds the level indicators of the firm characteristics discussed in the previous
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section which we denote by $D_{Ch,s}^{(Ch_s)}$, $s \in \{1, 2, \ldots, S\}$.

\[ EQ_i = \gamma_0 + \gamma^{(c)} \times D_i^{(SG&A)} + \gamma_1 \times D_i^{(Ch_1)} + \ldots + \gamma_s \times D_i^{(Ch_S)} + \epsilon_i \]  

(12)

The second regression yields consistent estimates, $\gamma^{(c)}$ (controlled), of the association between EQ measures and the SG&A intensity. It also indicates which of the fundamental firm characteristics are significantly associated to the EQ measures.

We structured the estimating set-up as follows. First, we divided the range of all (continuous) independent variables, that is, firm characteristics that might explain the EQ measure, in 30 intervals of equal probability (if the characteristic is discrete, like the number of recent loss years, each value defines a class). Then, we created 29 dummy variables indicating that the explaining characteristic belongs to each one of these intervals but one, the reference level. For ease of presentation, the reference interval consists of either the values around the median, when the dependent variable changes much with the level of the independent variable or the lowest values of the independent variable otherwise. A coefficient of the $j$-th indicator ($1 \leq j \leq 30$, reference level excluded) significantly different from zero provides statistical evidence on the difference between the mean EQ measures of firms with values of the firm characteristic in the $j$-th interval and the mean EQ measure of firms with value of the characteristic in the reference interval. Significant negative/positive coefficients indicate that the characteristic is associated with the EQ measure.

Given the large number of parameters involved and tests performed, the results of the analysis are presented through graphs instead of tables. For a given EQ measure and a given firm characteristic, we display three curves.
**Fig. 5:** Firm characteristics that explain the contemporaneous correlation between revenues and expenses. The figure displays the coefficients of the level indicators corresponding to the characteristics named in the title of the graph in the simple regression (11) (top-right: \( \gamma(u) \)) and in the multiple regression (12) (the other graphs), together with their 95% confidence intervals. We note that the association of the SG&A intensity is much reduced by controlling characteristics. The frequency of loss years shows, by far, the strongest association with the contemporaneous correlation between revenues and expenses. The asterisk marks the variables that subsume the SG&A intensity.

The first one traces the 29 coefficients of the indicator variables modeling the levels of the firm characteristic and is shown using a full line. The other two trace the lower and the upper limits of the 29 95% confidence intervals\(^\text{17}\) and are shown as dotted lines. Such a graph tests 29 hypothesis of equal mean EQ measure (that is, association of firm’s characteristic with the EQ measure),

\(^\text{17}\) The confidence intervals are based on heteroskedasticity-consistent (HC) estimation of the covariance matrix of the coefficient estimates in the regression model. Long and Ervin (2000) conduct a simulation study of HC estimators in the linear regression model (HC0 to HC3; HC0 is Whites estimator (White (1980)) while the other estimators are refinements of this), recommending to use of the so-called HC3 estimator which we used consistently through the analysis. Qualitatively identical results were obtain using alternative HC estimators.
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Fig. 6: Firm characteristics that explain the volatility of earnings. The figure displays the coefficients of the level indicators corresponding to the characteristics named in the title of the graph in the simple regression (11) (top-right: $\gamma^{(u)}$) and in the multiple regression (12) (the other graphs), together with their 95% confidence intervals. We note that the association of the SG&A intensity practically vanishes when controlling with other fundamental firm characteristics. The frequency of loss years shows the strongest association with earnings volatility, followed by CFO volatility. The asterisk marks the variables that subsume the SG&A intensity.

one for each of the levels 1 to 30 of firm’s characteristic, the reference level excepted. The tests are done by checking if 0, the null difference between the two mean EQ measures, belongs to each of the 29 confidence intervals.
Fig. 7: Firm characteristics that explain the expectation formation pertinence of earnings. The figure displays the coefficients of the level indicators corresponding to the characteristics named in the title of the graph in the simple regression (11) (top-right: $\gamma^{(u)}$) and in the multiple regression (12) (the other graphs), together with their 95% confidence intervals. We note that the association of the SG&A intensity practically vanishes when controlling with other fundamental firm characteristics. The frequency of loss years shows the strongest association with the EQ measure, followed by size. The asterisk marks the variables that subsume the SG&A intensity.

Figures 5, 6, and 7 display the results of the estimation of the specifications (11) and (12) for the volatility of earnings, the contemporaneous correlation between revenues and expenses and the expectations formation.
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pertinence of earnings, respectively. The first row of each figure displays the estimated coefficients $\gamma^{(u)}$ (uncontrolled) (left) and $\gamma^{(c)}$ (controlled) (right). The other graphs display the coefficients of the level indicators of the characteristics that are significantly associated to the corresponding EQ measure. The asterisk marks the variables that subsume the SG&A intensity.

Figure 5 shows that firms with higher frequency of loss years and firms with more volatile non-timing-related accruals (as measured by the SPI) have lower correlations of contemporaneous revenues and expenses. For this EQ measure, the SG&A intensity is subsumed by the frequency of loss years.

Figure 6 presents evidence that higher frequency of loss years, higher accounting profitability and higher economic risk (as measured by the volatility of cash flows from operations) are associated with higher earnings volatility. For this EQ measure, the SG&A intensity is subsumed by the frequency of loss years together with the economic risk measure.

Figure 7 suggests that earnings of smaller firms, those of firms reporting negative earnings and those of firms with high rate of asset growth inform less the expectation formation process. For this EQ proxy, the SG&A intensity is again subsumed by the frequency of loss years.

The three analyses reported in this section share two similarities. First, each shows that the association of intangible intensity to the EQ measure under discussion is largely spurious, that is, it mostly disappears when we control for profitability, growth and riskiness fundamental characteristics. Second, the frequency of loss years is the most important firm characteristic for explaining each of the three EQ measures under discussion. We will see in the next section that controlling for the loss year frequency greatly reduces the “listing effect” dynamic of the three EQ measures.
6.3 Firm characteristics that explain the evolution of the EQ measures

We note that, for a firm characteristic to contribute to explaining the evolution of a given EQ measure, it needs to satisfy two conditions. First, it should be significantly associated with the EQ measure and, second, it should have changed over time in a pattern similar to that of the measure. For example, even if the frequency of negative SPI is negatively associated to matching, its evolution does not show significant differences between cohorts. Consequently, changes in this firm characteristic will not be directly associated to the decline of the EQ measure. As we will see in the next section, the frequency of one-time losses is, nevertheless, related to the decline of the EQ measures indirectly, being associated to the frequency of loss years, the characteristic which explains the most of the EQ measures evolution.

In this section we investigate the degree to which the evolution of different firm characteristics is associated to the decline in the EQ measures. The results are presented in three similar figures, one for each of the EQ measures, each composed of four graphs. We explain now how these figures were produced.

For each of the three EQ measures we estimate the simple regression (8):

\[ EQ_{i,t} = \mu(t) + \beta(t) \times D_{i,t}^{(Co)} + \epsilon_{i,t}. \]

This step quantifies and tests the differences between averages of the EQ measure conditional on the cohort. The top-left graph of each figure report the coefficients

\[ \beta_j(t) = \mathbb{E}[EQ_{it} \mid Co_j] - \mathbb{E}[EQ_{it} \mid Co_0] \]
Fig. 8: Evolution of contemporaneous correlation between revenues and expenses for different cohorts - hypothesis tests. The curves track the coefficients $\beta_j(t)$ ($j$ from 1 to 4, color-coded: red, green, blue, and black, in increasing order) in the simple regression (8) (top-left) and in the multiple regression (9) where the controlling characteristic(s) appear in the title of the graphs (the other graphs), as a function of $t$, the year. The shaded areas dropping from (around) the curves $\beta_j(t)$, $j = 1, 2, 3, 4$, represent the 95% one-sided (two-sided) confidence bands for the difference $E[\text{corr}(\text{Rev}, \text{Exp})_t | \text{Co}_j] - E[\text{corr}(\text{Rev}, \text{Exp})_t | \text{Co}_0]$ (first graph) and $E[\text{corr}(\text{Rev}, \text{Exp})_t | \text{Co}_j, \text{Ch}] - E[\text{corr}(\text{Rev}, \text{Exp})_t | \text{Co}_0, \text{Ch}]$ (the other graphs). The $x$-axis outside shaded area $j$ is statistically significant evidence of lower correlation between revenues and expenses for firms belonging to the cohort $j$ with respect to the 1960-1969 reference $\text{Co}_0$. Controlling with SG&A intensity explains some of the differences between later cohorts and the reference while controlling with the number of loss years reduces them dramatically. Controlling with the set of two fundamental firm characteristics explains, practically, all the differences between the later cohorts and the 1960-1969 reference.

and their one-sided 95% confidence levels, as a function of $t$, the fiscal year.

They are color-coded: red for the 1970-1979 cohort, green for the 1980-1989 cohort, blue for the 1990-1999 cohort, and black for the 2000-2009 cohort (in
decreasing order for earnings volatility and expectation formation pertinence and in increasing order for matching).

For each of the three EQ measures we also perform three time series analyses based on the multiple regression (9)

$$EQ_{i,t} = \mu(t) + \beta(t) \times D_{i,t}^{(Co)} + \gamma(t) \times D_{i,t}^{(Ch)} + \epsilon_{i,t},$$

controlling first, for the SG&A intensity, second, for the frequency of loss years, and third for a measure-specific set of the firm characteristics that are significantly associated with the given EQ measure and that have changed over time in a “listing effect” pattern. The estimation of the multiple regressions brings evidence on the degree of association between changes in the fundamental characteristics documented in section 6.1 and the decline of EQ measures.

The other three graphs in each figure display the coefficients

$$\beta_j(t) = \mathbb{E}[EQ_t | Co_j, Ch \in S] - \mathbb{E}[EQ_t | Co_0, Ch \in S]$$

and their one-sided 95% confidence levels, as a function of $t$, the fiscal year as follows. The top-right graph corresponds to controlling for the level of SG&A intensity, the bottom-left, for the number of loss years in the recent history of the firm, and the bottom-right, for the measure-specific set of significantly associated firm characteristics. These sets are defined as follows:

$$\{\% \text{ of loss years, } \sigma(SPI)\}$$
Fig. 9: Evolution of earnings volatility for different cohorts - hypothesis tests.
The curves track the coefficients $\beta_j(t)$ ($j$ from 1 to 4, color-coded: red, green, blue, and black, in increasing order) in the simple regression (8) (top-left) and in the multiple regression (9) where the controlling characteristic(s) appear in the title of the graphs (the other graphs), as a function of $t$, the year. The shaded areas dropping from (around) the curves $\beta_j(t)$, $j = 1, 2, 3, 4$, represent the 95% one-sided (two-sided) confidence bands for the differences $E[\sigma(NI)_t | Co_j] - E[\sigma(NI)_t | Co_0]$ (first graph) and $E[\sigma(NI)_t | Co_j, Ch] - E[\sigma(NI)_t | Co_0, Ch]$ (other graphs). The $x$-axis outside shaded area $j$ is statistically significant evidence of higher volatility for the earnings of firms belonging to the cohort $j$ with respect to the 1960-1969 reference $Co_0$. Controlling with SG&A intensity does not explain much of the differences between cohorts and the reference while controlling with the number of loss years reduces them dramatically. Controlling with the set of five fundamental firm characteristics explains, practically, all the differences between the later cohorts and the 1960-1969 reference.

for matching,

$\{\% \text{ of loss years, Size, ROA, } \sigma(CFO)\}$
for earnings volatility, and

\[ \{\% \text{ of loss years}, \text{Size}, \text{AT growth}\} \]

for earnings expectations formation pertinence.

The shaded areas dropping from (or surrounding) the curves \( \beta_j(t) \), \( j = 1, 2, 3, 4 \), represent the 95% one-sided (two-sided) confidence bands for the difference

\[ \mathbb{E}[EQ_t|C_{oj}] - \mathbb{E}[EQ_t|C_{o0}] \]

in the top-left graphs or

\[ \mathbb{E}[EQ_t|C_{oj}, Ch \in \mathcal{S}] - \mathbb{E}[EQ_t|C_{o0}, Ch \in \mathcal{S}] \]

in the other graphs. The \( x \)-axis outside shaded area corresponding to the curve \( \beta_j(\cdot) \) is statistically significant evidence of lower EQ for firms belonging to the cohort \( j \) with respect to the 1960-1969 reference \( C_{o0} \). To put it shortly, the closer the four curves to 0, the more changes in the controlling fundamental firm characteristics explain the differences in the cohort EQ measures.

Figures 8, 9, and 10 present the results. They show that controlling with \( SG&A \) intensity explains some of the differences between cohorts and the reference while controlling with the number of loss years reduces them dramatically. Controlling with a set of fundamental firm characteristics (whose size ranges from two to four) explains most (if not all) of the differences between the EQ measures of later cohorts and those of the 1960-1969 reference.
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Fig. 10: Evolution of earnings’ expectation formation pertinence for different cohorts - hypothesis tests. The curves track the coefficients $\beta_j(t)$ ($j$ from 1 to 4, color-coded: red, green, blue, and black, in increasing order) in the simple regression (8) (top-left) and in the multiple regression (9) where the controlling characteristic(s) appear in the title of the graphs (the other graphs), as a function of $t$, the year. The shaded areas dropping from (around) the curves $\beta_j(t)$, $j = 1, 2, 3, 4$, represent the 95% one-sided (two-sided) confidence bands for the difference $E[EFP(NI_t | Co_j) - E[EFP(NI_t | Co_0)]$ for the first graph and $E[EFP(NI_t | Co_j, Ch) - E[EFP(NI_t | Co_0, Ch)]$ for the other graphs. The $x$-axis outside shaded area $k$ is statistically significant evidence of lower earnings’ pertinence for firms belonging to the cohort $j$ with respect to the 1960-1969 reference $Co_0$. Controlling with SG&A intensity does not explain much of the differences between cohorts and the reference while controlling with the number of loss years reduces them dramatically. Controlling with the set of three fundamental firm characteristics explains, practically, all the differences between the later cohorts and the 1960-1969 reference.

7 Relationship between accruals and cash flows over time

In a related paper Bushman et al (2016) investigate temporal changes in the correlation between accruals and cash flows. Although the goal is similar to
ours, their approach is very different. To disentangle the effect of correlated firm characteristics on the EQ measure, they rely on a combination of cross-sectional univariate and multiple regressions where the variables are adjusted $R^2$ from different regressions relating the correlation of cash flows and accruals and firms characteristics. The authors highlight a number of issues related to their approach. First, the explanatory variables they considered are highly correlated. The magnitude of correlations between the six explanatory variables ranges from 0.5 to 0.9. Second, the cross-sectional approach yields a very small sample. The time-series examined provide only 51 observations for each variable.

In this section we investigate the association between changes in the cash flow accrual correlation and those in fundamental firm characteristics using the approach developed in section 4.2 and 4.3. First we investigate the pattern of change in this EQ. As before, we display the mean value of the cash flow accrual correlation conditional on the cohort and year. The conditional mean is calculated on a moving window of size 5. This results in five curves describing the change over time of the cohort-specific average correlation.

The first graph in Figure 11 shows a decrease in the magnitude of the cash flow accrual correlation. The pattern of change is different from that of the other EQ measures displayed in Figure 2. The attenuation is the result of a mixture of the “listing effect” due to later cohorts, that is, cohorts 3, 4, and 5, and a slow and continuous trend visible in the earlier cohorts evolution. It is worth noting the common dynamic of the first two cohorts. The later patterns seems more ample and probably would dominates the former in a less sensitive analysis. This most likely explains why Bushman et al (2016) find that “the documented attenuation in the accrual-cash flow
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Cash flow accrual correlation

Volatility of NOPI+SPI

Fig. 11: Time evolution of accruals and cash flow correlation. The plots display cohorts’ mean of the $\text{corr}(CFO, TACC)$ (left) and of $\sigma(SPI + NOPI)$, the volatility of one-time and non-operating items (one of the variables that explain the time evolution of the EQ measure, see Bushman et al (2016)) (right) estimated on a 5 year moving window. The pattern of change is different from that of the other EQ measures (see Figure 2). The decrease in the EQ measure is the result of a mixture of the “listing effect” due to later cohorts and a slow and continuous trend visible in the earlier cohorts.

Relation is not driven by the change in the sample composition, in contrast to the findings of Srivastava [2014] for earnings quality metrics”.

Bushman et al (2016) find that “one-time and non-operating items and loss firms are mostly responsible for the attenuation in the overall correlation between accruals and cash flows” and that the effect of temporal changes in intangible intensity “is subsumed by other explanatory variables”. The second graph in Figure 11 displays the pattern of change in the volatility of one-time and non-operating items while the evolution of the frequency of loss-years is shown in Figure 3. We note the similarity between the patterns of change in the EQ measure under scrutiny and the former fundamental firm characteristic.

To evaluate these claims we perform the regression in (11) where the independent variables are the levels of the SG&A intensity followed by a regression of the type in equation (12) where the variables competing to
explain the cash flow accrual correlation are the frequency of loss-years and the volatility of one-time and non-operating item.

Following the practice developed in section 6.2, Figure 12 displays on first row the estimated coefficients $\gamma^{(u)}$ (uncontrolled) (left) and $\gamma^{(c)}$ (controlled) (right) of the levels of $SG&A$ intensity. The other graphs display the coefficients of the level indicators of the frequency of loss years and the volatility of one-time and non-operating items. The graphs show that the negative association of the $SG&A$ intensity to the cash flow accrual correlation (higher $SG&A$ intensity corresponds to less negative correlation) is

Fig. 12: Firm characteristics that explain the correlation between cash flows and accruals. The figure displays the coefficients of the level indicators corresponding to the characteristics named in the title of the graph in the simple regression (11) (top-right: $\gamma^{(u)}$) and in the multiple regression (12) (the other graphs), together with their 95% confidence intervals. We note that the association of the $SG&A$ intensity is much reduced by controlling characteristics. The frequency of loss years shows, by far, the strongest association with the correlation between cash flows and accruals. The asterisk marks the variables that subsume the $SG&A$ intensity.
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strongly reduced by controlling with the levels of the other two fundamental firm characteristics. As before, the frequency of the loss years is the most important explanatory variable. Its effect levels off at around a 0.4 increase in the correlation for the firms with more than three years of losses within the 8 year history. In the case of this EQ measure the $SG&A$ intensity is subsumed by the frequency of loss years.

Next, we analyze how changes in the two fundamental firm characteristics are related to the time evolution of the cash flow accrual correlation.

First graph in figure 13 shows significant differences in the level of cash flow accrual correlation between successive cohorts. The second graph indicates that controlling for the level of $SG&A$ intensity explains a small part of the incremental discrete pattern of change between cohorts. Controlling with the frequency of loss years addresses most of the incremental changes brought by the more recent three cohorts while adding the volatility of one-time and non-operational income items as a control seems to explain practically all of the incremental difference.

Our results refine and complete the analysis in Bushman et al (2016). We confirm their conclusion that “the attenuation of the accrual-cash flow relationship is prevalent both among old and new economy firms”. However, we refine their statement that “the documented attenuation in the accrual-cash flow relation is not driven by the change in the sample composition, in contrast to the findings of Srivastava (2014) for earnings quality metrics” by showing that the pattern of change is a mixture of common decline for the older cohorts and incremental change brought by the more recent cohorts. Most importantly, we confirm their two central findings. First, an increase in one-time and non-operating items, and loss firm years, explain (practically
C. Starica, J. Kang

Fig. 13: Evolution of correlation between cash flows and accruals for different cohorts - hypothesis tests. The curves track the coefficients $\beta_j(t)$ ($j$ from 1 to 4, color-coded: red, green, blue, and black, in increasing order) in the simple regression (8) (top-left) and in the multiple regression (9) where the controlling characteristic(s) appear in the title of the graphs (the other graphs), as a function of $t$, the year. The shaded areas dropping from (around) the curves $\beta_j(t)$, $j = 1, 2, 3, 4$, (the dotted lines in the graphs on the left) represent the 95% one-sided (two-sided) confidence bands for the difference $E[\text{corr} (\text{CFO}, \text{TACC})_t | Co_j] - E[\text{corr} (\text{CFO}, \text{TACC})_t | Co_0]$ (first graph) and $E[\text{corr} (\text{CFO}, \text{TACC})_t | Co_j, Ch] - E[\text{corr} (\text{CFO}, \text{TACC})_t | Co_0, Ch]$ (the other graphs). The x-axis outside shaded area $j$ is statistically significant evidence of lower correlation between cash flows and accruals for firms belonging to the cohort $j$ with respect to the 1960-1969 reference $Co_0$. Controlling with SG&A intensity explains little of the differences between cohorts and the reference while controlling with the number of loss years reduces them dramatically. Controlling with the set of two fundamental firm characteristics explains, practically, all the differences between the later cohorts and the 1960-1969 reference.

all of) the cohort differences in the association between accruals and cash flows. Second, the association between the cash flow accrual correlation and
the SG&A intensity is not significant being subsumed by other explanatory variables (more precisely, by the frequency of loss years).

8 Conclusions

The last decades have witnessed significant changes in the business environment with important consequences on the fundamentals of firms. An increase in business competitiveness and uncertainty lead to a dramatic rise in the idiosyncratic risk of the typical stock. Changes to the fundamental economics of new firms seeking capital gave weaker firms and firms whose expected payoffs are further in the future access to public equity financing. As the US economy moved towards a knowledge based economy, there was a significant increase in the levels of intangible capital. As a consequence, newer listings, in particular, are characterized by higher average intangible intensity.

These changes were paralleled by developments in the quality of reported earnings. While the literature seems to agree on the existence of a downward trend in many of the EQ measures, there is disagreement about the explanation of this evolution.

In a seminal contribution, Srivastava (2014) argues that most of the changes in three important EQ measures, that is, earnings volatility, the matching of revenues and expenses, and the value relevance of earnings, over the last decades can be attributed to “the widening gap between the intangible intensities of the new- and seasoned-firm segments” as a result of the evolution of the US economy from an industrial to a knowledge economy.

In a related paper, Bushman et al (2016) find that one-time and non-operating items and loss firms are mostly responsible for the attenuation in the overall correlation between accruals and cash flows, another commonly
used measure of EQ quality. Most importantly, in a multiple regression analysis, the authors find that the effect of temporal changes in intangible intensity is not significant, being subsumed by other explanatory variables.

In contrast to Srivastava (2014), Donelson et al (2011) argue that the decline in matching of revenues and expenses is primarily attributable to an increase in the incidence of large special items associated to increased competition in the U.S. economy.

In this paper we have provided a unifying perspective on these apparently contradictory findings and relate the evolution of the EQ measures to changes in firm’s profitability, non-timing-related accruals, growth and economic risk.

We also brought strong evidence that the identification in Srivastava (2014) is due to an analysis affected by omitted variable bias. While significantly negative when considered alone, the impact of intangible intensity disappears when controlling for other fundamental characteristics, as size, measures of profitability, growth and riskiness.

To summarize, we propose an alternative to the narrative developed in Srivastava (2014) which places the evolution towards a “21st century firm” characterized by higher knowledge intensity at the origin of the progressive lessening of earnings quality. Our account associates the decline in the EQ measures, to a greater extent, with the arrival to the market of riskier, less profitable firms, phenomenon most likely due to changes in the fundamental economics of new firms seeking capital (Fama and French (2004)) and to the increase in financial sophistication of the U.S. capital markets (Brown and Kapadia (2007)), and to a lesser extent, to the ever higher competitive economic environment in which the businesses have been evolving in the last 40 years or so (Irvine and Pontiff (2009)).
The issue of which of the two narratives is more likely reaches beyond the pure academic quest for truth as they imply opposing appraisals of current accounting reporting. If the increase in intangible intensity is the cause, the decline in EQ measures might be seen as a sign of failing accounting standards, ill-suited for quantifying and recording the risks and returns of intangible investments. If, contrary, the explanation for lower EQ lies with the facilitated access to public equity financing of weaker firms and firms whose expected payoffs are further in the future, then the evolution of the EQ measures can be interpreted as an expression of a well-functioning accounting standard that accurately reflects the increased weaknesses in the firm population. Our evidence points strongly towards the second assessment.

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Appendices

A Consistent estimation of the economic relation in RI model

Let us start by recalling the definition of a regression:

**Definition 1** The decomposition:

\[ Y = f(X) + \epsilon \]
is called a *regression* if and only if
\[
f(X) = E[Y|X]
\]
or equivalently, if the orthogonality condition
\[
E[\epsilon|X] = 0 \quad (13)
\]
holds.

Condition (13) guarantees that the regression function \(f\) can be consistently estimated using proven methods from the field of non-parametric regression like the ones presented in the next section B.

We state now the main result in Kang and Starica (2016).

**Proposition 1** *(Theoretical frame of expectation formation pertinence)*

1. For any set of predictors of future \(RI\), there exists a specification of the \(RI\) valuation model that is a regression\(^{18}\) of prices on the observed values of the predictors

   Suppose prices are given by equation (1) and let \textsc{predict}.\(RI\) be a set of predictors of the future residual earnings (as specified above). Then there exist \(m_{i,0}\) and \(m_{i,0}\), two possibly non-linear, firm-specific functions and \(\epsilon_{i,0}\) and \(\epsilon_{i,0}\), two error terms, such that:

   \[
P_{i,0} - B_{i,0} = m_{i,0}(\textsc{predict}.\textsc{RI}_{1,0} ; B_{i,0}, r_{i,0}) + \epsilon_{i,0} \quad (14)
   
   \text{and}
   
   P_{i,0}/B_{i,0} - 1 = m_{i,0}(\textsc{predict}.\textsc{RI}_{1,0} ; r_{i,0}) + \epsilon_{i,0}, \quad (15)
   
\(^{18}\) In the sense of the above definition.
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where

\[ E[\epsilon_{i,0} \mid \text{PREDICT.RI}_{i,0}] = 0 \quad \text{and} \quad E[\epsilon_{i,0} \mid \text{PREDICT.RI}_{i,0}] = 0. \] (16)

The functions \( m_{i,0} \) and \( m_{i,0} \) are specific to the set \( \text{PREDICT.RI} \).

2. The regression functions are valuations incorporating expectations shaped only by the current values of the predictors

Moreover,

\[
m_{i,0}(\text{PREDICT.RI}_{i,0} ; B_{i,0}, r_{i,0}) := \sum_{t=1}^{\infty} \frac{E[R_{i,t} \mid \text{PREDICT.RI}_{i,0}]}{(1 + r_{i,0})^t}
\]

and

\[
m_{i,0}(\text{PREDICT.RI}_{i,0} ; r_{i,0}) := \sum_{t=1}^{\infty} \frac{E[R_{i,t} / B_{i,0} \mid \text{PREDICT.RI}_{i,0}]}{(1 + r_{i,0})^t},
\]

i.e. the regression function in the decomposition (14) and (15) represent a valuation incorporating expectations of future abnormal earnings formed only on the basis of the current values of the predictors \( \text{PREDICT.RI} \).

3. The error term is a measure of expectation formation pertinence of the predictors set

The error terms in the decomposition (14) and (15), \( \epsilon_{i,0} \) and \( \epsilon_{i,0} \), amount to an adjustment due to other available information to a price set upon expectations shaped only by the observed values of the predictors \( \text{PREDICT.RI} \). As such, their sizes reflect the extent to which these values inform the expectations of future earnings incorporated in prices.

The notation \( m_{i,0}(\cdot ; \cdot) \) and \( m_{i,0}(\cdot ; \cdot) \) in (14) and (15) emphasizes the fact that the regression functions depend both on a number of variables and on a number of parameters. The variables, that is \( \text{PREDICT.RI}_{i,0} \), are listed before
the semicolon while the parameters, \((B_{i,0}, r_{i,0})\) for \(m_{i,0}\) and \(r_{i,0}\) for \(m_{i,0}\), are listed after. Moreover, the regression functions are predictor-set specific.

Kang and Starica (2016) further argue that one can assume that the (non-linear) functions \(m_{i,0}/m_{i,0}\) for firms \(i\) in the same industry \(I\), of similar size \(S\) and level of conservative accounting \(C\) are approximately equal:

\[
m_{i,0}(\cdot) \approx m_{I,0}(\cdot; S_i, C_i) \quad \text{and} \quad m_{i,0}(\cdot) \approx m_{I,0}(\cdot; S_i, C_i), \quad i \in I.
\]

This assumption has two consequences. First, it allows for consistent estimation of \(m_{I,0}/m_{I,0}\) in cross-sections\(^{19}\). Second, it indicates the need to include size and the level of conservative accounting as extra parameters in the valuation regression functions when inferred cross-sectionally.

The literature on non-parametric regressions shows that conditions (16) guarantee that the specifications of the RI valuation model in (14) and (15) can be consistently estimated (Györfi et al (2002)). The issue of omitted variable bias is structurally ruled out.

**Corollary 1 (Consistent estimation of economic relation in RI model)**

The functions \(m_{i,0}\) and \(m_{i,0}\) in the regression specifications of the RI valuation model (14) and (15) can be consistently estimated using proven methods from the field of non-parametric regression.

The next section presents some common non-parametric estimation techniques.

\(^{19}\) Without the relative constancy of the function \(m_{i,0}\) on industries, one needs to estimate it from the time-series of individual firm observations which would strongly bias the sample towards survivor firms. The industry-approach requires only a sufficient size cross-section of firms in a given industry at a given point in time. A second viable option estimates \(m_{I,0}/m_{i,0}\) on a a panel-type sample combining time series with cross-sectional observations. One achieves this way a sample that is large enough for statistical precision limiting nevertheless the issue of the survival bias.
B Non-parametric regression estimation

The AM and PPR model belongs to the first alternative paradigm to linear regression. AM is a powerful and yet simple technique. They were introduced by Hastie and Tibshirani (1986). The AM framework is based on an two appealing and simple assumptions. First, the relationships between the individual predictors and the dependent variable follow smooth patterns (that can be linear or non-linear). Second, we can estimate these smooth relationships simultaneously and then predict the dependent variable by simply adding them up.

\[
E(Y|X) = \alpha + s_1(X_1) + \ldots + s_p(X_p), \tag{17}
\]

where \( Y \) is the dependent variable, \( E(Y|X) \) denotes the expected value of \( Y \) conditional on \( X \). The terms \( s_1(X_1), \ldots, s_p(X_p) \) denote smooth, non-parametric functions. Note that the shape of predictor functions are fully determined by the data as opposed to parametric functions that are defined by a typically small set of parameters. This allows for more flexible estimation of the underlying regression patterns without knowing upfront what these patterns look like. Moreover, this helps us find patterns we may have missed with a parametric model. Predictor functions are automatically derived during model estimation.

The PPR model fits a global non-linear regression model to the data by first projecting the matrix of explanatory variables in a directions that optimizes the model fit before applying smoothing functions to the projected explanatory variables. As a new projection is found, the data are reduced by removing the component along that projection, and the process of finding a new projection is repeated. This is the ”pursuit” aspect that gives the name to the technique. The final model looks like

\[
Y = \beta_0 + \sum_{j=1}^{r} f_j(\beta'_j X) + \varepsilon, \tag{18}
\]
where $X$ are the independent variables (in number of $p$), $\beta_j$ is a collection of (unknown) directions, $f_j$ are univariate non-linear regression functions to be estimated while $r$ is the number of modeled smoothed non-parametric functions to be used as constructed explanatory variables. The value of $r$ is found through cross-validation.

In words, PPR fits non-linear functions $f_j$ of linear combinations in the explanatory variables $X$. For large values of $r$ and an appropriate set of functions $f_j$, the PPR approach can estimate any continuous function in $\mathbb{R}^p$.

The other two techniques we use belong to the second alternative to linear regression: that where one partitions the independent variable space into smaller regions where the relation between the regressors and the regressed is more manageable and one fits on each region a simple linear models. The main ingredient of such an approach is the recursive partitioning of the variables space to regions small enough to display a simple structure to which we can fit simple models. This alternative approach to linear regression yields the class of recursive partitioning regression models.

Regression trees use the concept of a tree to represent the recursive partition. Each of the terminal nodes of the tree represents a cell of the partition and has attached to it a simple model which applies in that cell only. Both models under discussion admit a tree representation: CART fits local constants while MARS fits piece-wise linear regressions.

For classic regression trees (CART), the model in each cell is just a constant estimate of $Y$. That is, suppose the points $(x_1, y_1), (x_2, y_2), \ldots (x_c, y_c)$ are all the data points in a given cell. Then our estimated model for the cell is just

$$\hat{Y} = \frac{1}{c} \sum_{i=1}^{c} y_i,$$

i.e., the sample mean of the dependent variable for the data points in that cell. This is a piece-wise-constant model. There are several advantages to this approach.
Making predictions is fast: just look up constants in the tree. It is easy to understand which explanatory variables are important by look at the tree structure. Since the model yields a jagged response, it can work when the true regression surface is not smooth. If the regression surface is smooth, the piece-wise-constant response surface can approximate it arbitrarily closely. Moreover, there are fast and reliable algorithms to construct the trees.

MARS extends the linear models to automatically consider non-linearities and interactions between variables. The models has the following form

\[ Y = \sum_{i=1}^{k} c_i B_i(X) + \varepsilon \]  

where \( B_i(x) \) are basis functions and \( c_i \) unknown coefficients (to be estimated). The basis functions are constants, univariate functions of the form \( \max(0, x - \text{const}) \) called \textit{hinge functions} or (multivariate) products of two or more hinge functions. In words, the model is a weighted sum of non-linear basis functions \( B_i(X) \). The parameters of the non-linear basis functions as well as their weights need to be estimated.

MARS automatically selects variables, the values of the constants in the basis functions and estimates the coefficients \( c_i \). The hinge functions automatically partition the input data, so the effect of outliers is reduced. MARS is flexible enough to model non-linearity and variable interactions, yet the constrained form of basis functions prevents too much flexibility.


References

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