Financial development, intangible investments, and the evolution of earnings quality

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Abstract

We contribute to the ongoing debate on the reason for the decline in earnings quality (EQ) documented by prior literature. We argue that Srivastava (2014)'s explanation that "each new cohort of listed firms exhibits lower earnings quality than its predecessors, mainly because of higher intangible intensity" may not be satisfactory. Instead, we assert that the downward trend in the EQ measures of successive cohorts reflects a progressive decrease in newer firms' business effectiveness, as measured by profitability, operational efficiency, and economic risk. This is a direct result of easier access to public funding brought about by the 1970s trend change in the state of development of the U.S. financial sector (Rajan and Zingales, 2003). Our explanation strictly encompasses Srivastava (2014)'s. While for newcomers in specific industries lower business effectiveness is associated with higher intangible intensity, the lack of fit of most of the new listings is not explained by their investments in intangibles. They are simply weaker, riskier firms and have lower EQ as a result.

Key words: Earnings quality, financial development, intangible investments, business effectiveness, economic risk, cohorts

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1. Introduction

Previous literature has documented a sustained decline in earnings quality (EQ) of US listed firms over the past few decades with each new cohort exhibiting lower EQ than the predecessors. This evolution could be associated with a number of different macroeconomic scenarios. One popular explanation put forth by Srivastava (2014) claims that the advancement towards a "21st century firm" characterized by higher knowledge intensity is responsible for the gradual decrease of EQ of successive cohorts. The argument supporting this claim states that the biggest factor in the decline of three commonly-used EQ measures (earnings volatility, matching of revenues and expenses, and value relevance of earnings) is "the widening gap between the intangible intensities of the new- and seasoned-firm segments" (page 198).

In this paper, we refine the analysis in Srivastava (2014) and argue that this explanation may be only part of the story. More concretely, we put forward evidence that a trend change in the state of development of the U.S. financial sector is the most likely cause of the evolution of the EQ measures of successive cohorts. After a long period of decline, the general direction of the financial sector's development turned positive in the 1970s, significantly facilitating access to public equity funding for privately-owned firms (Rajan and Zingales, 2003). Consequently, increasingly weaker firms as well as those with riskier expected payoffs became publicly traded (Fama and French, 2004). We argue that the decrease in EQ measures of successive cohorts directly reflects this steady decline in the business effectiveness of the evolving cross section of public firms. The gradual progression towards a lower degree of business effectiveness affects all industries, independent of the level of intangible expenditures. Most importantly, this evolution has subsumed the impressive increase in intangible intensity over the past four decades, which we document to be manifest in only a few industries.

The financial economic literature emphasizes the importance of financial development for understanding the evolution of the world's economies over the twentieth century. A large body of evidence indicates that the development of a country's financial sector greatly facilitates its economic growth. In a seminal paper, Rajan and Zingales (2003) put forward evidence that the state of development of the financial sector has not changed monotonically over time. Rather, the indicators of financial development at first fell and then rose between 1913 and 1999. While difficult to date precisely, the turning point seems to lie somewhere in the 1970s. Since then, there has been a marked revival of U.S. financial markets, triggering significant structural changes in the cross section of listed firms.

Studies of larger samples of countries support the idea that financial development facilitates the entry of newcomers onto the public market by making public funding more available. As a direct consequence, the average business fit goes down within the cross section of listed firms. Looking at the U.S. economy, Fama and French (2004) point out that after 1979, "weaker firms and firms whose expected payoffs are further in the future become viable candidates for public equity financing." Their evidence suggests that development of the U.S. financial sector has brought about a downward shift in the supply curve for newly listed equity funding, resulting in a lower cost of equity, which has the direct consequence of increasing both new lists and the proportion of weak new lists. In particular, cheaper capital allows new firms pursuing intangible intensity technologies, i.e., technologies with more distant future payoffs and higher reward uncertainty, to come to market. In other words, their evidence suggests an encompassing relationship between the two macroeconomic developments under discussion. Advances in the financial sector (which facilitate the entry of newcomers on the market) subsume the trend towards new arrivals with higher levels of intangible intensity .

We complement the evidence in Fama and French (2004) supporting the hypothesis of a progressive decrease in the fit of newcomers.[1] More precisely, we document an economy-wide decrease in firms' business effectiveness as measured by three firm-specific characteristics: profitability, operational efficiency, and economic risk. We also show that the decrease in firm-specific business effectiveness is concentrated in the newly traded part of the economy. The average business effectiveness of cohorts of market arrivals decreases successively. Further, the sequential decrease in business effectiveness for newer cohorts is economy-wide, i.e., it affects both high and low intangible intensive industries.

Next, we put forward evidence that lower business effectiveness is associated with lower EQ measures. Finally, in a dynamic analysis, we show that the decline in EQ of successive cohorts is associated with the economy-wide gradual decrease in the business effectiveness of firms. Controlling cross-sectionally for proxies of firms' business effectiveness explains most of the decline in EQ measures.

We might ask how our findings can be reconciled with the results in Srivastava (2014). We provide two responses: one conceptual, the other, statistical. Conceptually, the answer lies in the encompassing relationship existing between business effectiveness and intangible intensity, as suggested by Fama and French (2004). High intangible intensity is associated with low business effectiveness, while the opposite is not true. Intuitively, research and development (*R&D*), advertising, and human capital spending that generate intangi-

[1] This process extends over the last three decades of the twentieth century and comes to an end around the year 2000 (Doidge et al., 2018).

ble assets are inherently associated with more uncertain outcomes in generating sales and positive cash flow, which translate into lower profitability and efficiency and/or higher economic risk. In addition, the immediate expensing of these expenditures directly lowers the accounting profitability of firms and has an unmediated impact on both efficiency and economic risk measures. However, low business effectiveness does not presuppose high intangible investments. We argue that for most of the newcomers, their lower business effectiveness is in fact not explained by investments in intangibles. Instead, they are simply less profitable, less efficient, riskier firms.

Statistically, if the observed trend in EQ is explained by the decline in newer cohorts' business effectiveness, which for some of the firms in the cross section is associated with (and possibly accentuated by) increased intangible expenditures, a regression analysis of the EQ measures that takes into account intangible investments without considering the encompassing business effectiveness would find a significant association between the former and the dynamics of EQ by virtue of the *omitted variable bias* effect. In statistical terms, the analysis does not consider the true determinant (business strength) as an explanatory variable. Instead, it regresses the EQ measures on a variable correlated with the determinant (intangible intensity). This causes a bias in the coefficient of the correlated variable, which spuriously[2] becomes significant. As soon as business effectiveness is included in the analysis, the association with intangible intensity disappears, as the bias is taken care of by the inclusion of the true determinant. Our analysis shows exactly that.

We bring forward three types of evidence in support of the explanation on the relation between our findings and the results in Srivastava (2014). First, we show that low

[2]Intangible intensity bears association with EQ only due to its correlation with the determinant business strength and because the latter is not taken into account.

business effectiveness is associated with higher intangible intensity only for a minority of the firms in the newer cohorts, concentrated in the high-tech and medical industries. The rest of the newcomers, constituting up to three-quarters of the cohorts, show lower average business effectiveness matched by no change in the level of intangible investments. Second, we show that, while significantly negative when considered alone, the association between Srivastava (2014)'s proxy for intangible intensity (as well as that of other intangible investment measures) with the three EQ proxies disappears when we control for firm's characteristics measuring business effectiveness.

Third, if a decline in business effectiveness is the cause of lower EQ, controlling for the higher intangible intensity of newer cohorts would only control for a part of the decline in business effectiveness and hence only explain a part of the decrease in EQ measures. Controlling for the level of business effectiveness should in contrast remove the majority of differences between consecutive cohorts of new arrivals. We observe both of these consequences.

As a by-product of our analysis, we refine the accepted perspective on the evolution of intangible investments as put forwards by Srivastava (2014), who states that "the increase in intangibles represents a shift in the firm population toward intangible-intensive firms due to new listings, rather than a general increase in the intangible intensity of all firms." Our analysis indicates that, while newer cohorts do display ever higher median intangible intensity (up to the 2010 cohort), this progressive increase is due only to the (newer) firms in a few industries, i.e., the hi-tech and medical industries. All other newcomers, representing between 55% and 85% of the newer cohorts, show no increase in their average intangible intensity. In other words, the successive increase in the intangible intensity of newer cohorts is not at all a general occurrence affecting all new firms arriving to the market. It is instead concentrated to a few high intangible intensity industries, while the most of the economy demonstrates no upper trend.

To present evidence supporting our alternative explanation, we make use of a methodological novelty by redefining the EQ measure that quantifies the association of earnings to prices. Srivastava (2014) measures this association based on the adjusted R^2 of the yearly regression of stock returns on earnings and changes in earnings (Easton and Harris, 1991; Lev and Zarowin, 1999). Such a measure is constant for all firms in a cross section and, hence, is not suited to the conditional analysis needed to disentangle the impacts of the changing firm characteristics competing to explain the downwards trend in the association between earnings and prices. Such an analysis regresses the EQ measures on competing firm characteristics (intangible intensity vs. business effectiveness) and requires a regressand that is firm-specific.

As a remedy, we use the expectation formation pertinence (EFP) research design (Starica and Marton, 2020, section 7), which decomposes prices into a valuation incorporating expectations of future income formed only on the basis of the level of reported earnings plus an investors' adjustment reflecting other information. 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 firm-specific: each firm year is characterized by a specific valuation error.

Furthermore, our analysis and the presentation of results draw extensively on the use of graphs which allow for nuanced description of the economic relations in focus as well as for efficient presentation of results of a large number of statistical tests. We think of this choice as an example of how scientific practice from neighboring fields (econometrics, time series) can enrich the current accounting research methodology. The graphical presentation saves space and facilitates the interpretation of the statistical analysis.

We want to emphasize that the choice of presenting our results graphically instead of using tables (which is the norm in accounting literature) does not diminish in any way the rigor of our statistical analysis. The two approaches give the reader the same information. Cross-sectional point estimates corresponding to the years in the sample (which would be reported as values in a table) become curves while tabulated standard errors of estimates are reported as the width of the confidence intervals that surround the curves of point estimate. Testing the hypothesis that a point estimate is equal to 0 becomes extremely easy and intuitive as it is equivalent to visually checking if 0 (the x-axis) belongs to (crosses) the confidence interval displayed by the graph.

2 . The evolution of EQ measures and its macroeconomic explanation

This section sets up the conceptual framework for the analysis that puts to test the likelihood of the two competing explanations for the documented decrease in EQ measures of successive cohorts over the past few decades.

2 .1. Changes in EQ measures

Previous accounting literature has documented a sustained decrease in the quality of earnings manifested in a decline in their relevance to prices (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 in an increase in their volatility (Givoly and Hayn, 2000; Dichev and Tang, 2009). More recently, Srivastava (2014) has shed light on the nature of the decline of three EQ measures by documenting 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 so-called *new listing* phenomenon (Brown and Kapadia, 2007). In other words, most of the observed decline in EQ measures reflects changes in the cross section of firms.

This finding naturally requires an explanation. *In what ways has the sample changed? Along which dimensions (relevant to their EQ) do newer arrivals differ from older firms? What macroeconomic developments drive the changes in the cross-sectional structure of listed firms that leads to lower EQ?* Our paper discusses two competing narratives (an established one and a challenging new explanation), which we outline in the following.

2 .2. Evolution towards a 'knowledge economy' explains the decline in EQ measures

Srivastava (2014) argues that the macroeconomic process at the root of the decrease in EQ is the evolution of the U.S. economy from an industrial towards a knowledge-based economy. The result of this evolution is visible in firms' average intangible intensity as measured by *R&D* expenses, market-to-book ratios, and *SG&A*, which are proxies for the level of intangible investments and show a dramatic increase over time.

The immediate expensing of intangible investments may reduce matching. Further, the yearly variation of these should increase the volatility of earnings, as revenue fluctuations do not match those of intangible investments. In addition, the variability in the earnings of intangible-intensive firms might be augmented due to higher uncertainty about the future benefits of their investments (Kothari et al., 2002). More volatile earnings are harder to predict. Consequently, current level of earnings might be less informative for price formation.

The analysis in Srivastava (2014) uses *SG&A* intensity as a proxy for intangible intensity because "firms typically expense in-house intangible expenditures through SG&A accounts" 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."

2 .3. *Trend change in the state of development of the financial sector explains the decline in EQ measures*

In a seminal paper, Rajan and Zingales (2003) argue that "the state of development of the financial sector does not change monotonically over time." They instead document a U-shaped evolution in the level of financial development , which has its nadir around 1980. Since then, there has been a revival of financial markets. Rajan and Zingales (2003) define financial development as a measure of "the ease with which any entrepreneur or company with a sound project can obtain finance, and the confidence with which investors anticipate an adequate return." For equity markets, the inflection of the trend implies that access to public financing becomes easier and, consequently, a greater fraction of the economy becomes publicly held (Brown and Kapadia, 2007). As a result, "weaker firms and firms whose expected payoffs are further in the future become viable candidates for public equity financing," as documented in Fama and French (2004).

The latter cited paper also identifies the most likely mechanism through which financial development induces structural changes in the composition of the listed cross section of firms. Namely, a downward shift in the supply curve for funding of the new list lowers the expected return, resulting in positive market values for weaker firms and those with more distant future payoffs. This shift occurs slowly during the 1980s and 1990s and results in progressively more left-skewed profitability and operational efficiency in newly listed firms (Fama and French, 2004) as well as in a significant reduction in cash flows, which also become more volatile (Brown and Kapadia, 2007; Irvine and Pontiff, 2009). To summarize, the extension of public financing to a greater fraction of the economy leads to a progressive deterioration of fundamental characteristics related to firm business effectiveness, namely, profitability, efficiency, and economic risk (cash flow volatility).

Around the year 2000, financial development enters a new phase characterized by a decrease in the net benefit of being listed, in particular for firms with unproven intangible assets (Doidge et al., 2017). As a result, the number of listed firms decreases, resulting in a U.S. “listing gap”, compared to non-U.S. countries as well as to its own past. We document that the cross-sectional decrease in number of listed firms in our sample is matched by a decline in the proportion of high intangible intensity firms in the cohort as well as in the level of intangible investment of the cohort[3]. The trend towards fewer newcomers in the public market and, in particular, towards fewer high intangible intensity new lists is consistent with the hypothesis put forth in Kahle and Stulz (2017) of a new phase in U.S. financial development according to which high intangible intensity firms “can be financed more efficiently through private sources than through public capital markets because the intrinsic properties of intangible assets make it more costly for them to be financed publicly.”

We also document that the process of progressively decreasing business effectiveness associated with the phase of financial development that brought a greater fraction of the economy into public ownership continues even in the newer phase in which private financing has become more attractive for a portion of the young firms. This finding supports our assertion that it is not the increase in *SG&A* intensity that causes the decrease in *EQ* measures. For the 2000–2010 cohort, the *SG&A* intensity decreased significantly with respect to previous cohorts, while the *EQ* measures fell to new low levels.

[3] In our sample, the percentage of high intangible intensity firms in the most recent cohort, i.e., the firms that came to market in the decade from 2000–2010, as well as the average selling, general, and administrative expenses (SG&A) intensity (citeanup2014’s proxy for the level of intangible expenditure) of the cohort decreased to the level of 1990.

The fact that the trends in EQ and business effectiveness measures are not affected by the end of the U.S. public market expansion also supports the hypothesis of a change in the importance of exchanges for the U.S. economy proposed in Doidge et al. (2017). According to the authors, the lower number of listed firms is not due to a decrease in "the ease with which any entrepreneur or company with a sound project can obtain finance" (which is the meaning that Rajan and Zingales (2003) give to the term "financial development") but rather to a change in the sources of funding. In other words, it could be that "the decrease in the net benefit of being listed is mostly related to developments in financial markets that make it easier for firms to thrive without being listed." According to this scenario, the decrease in the number of listed firms is a positive development in that it is the consequence of easier and possibly more efficient access to capital. As such, the "eclipse of the public markets as the place where young, successful, American companies seek their funding" (Doidge et al., 2018) is unlikely to bring about changes in the dynamics of EQ and business effectiveness measures or in their association (brought about by the previous phase of public market expansion), as a part of the funding simply switches from public to private.

Let us summarize the second narrative. The development of the U.S. financial market makes it so that progressively less effective firms gain access to financing (public in the first phase, public and private in the second). This lower business effectiveness manifests as lower profitability, lower operational efficiency, and higher economic risk (as measured by cash flow volatility) and translates into lower EQ measures (earnings volatility, matching of revenues and expenses, or earnings relevance to prices). For example, firms with higher economic risk, i.e., more volatile cash flows, tend to have more volatile earnings (Lang et al., 2006; Barth et al., 2008). Volatile cash flows also make earnings more difficult to forecast (Dichev and Tang, 2009). Consequently, the relevance of earnings numbers to the price formation decreases. Lower operational efficiency and higher volatility of cash flows make matching of revenues and expenses a more challenging task for the enterprise (see the formal argument in Section 4 .2 as well as the empirical evidence in Section 6 .1).

2 .4. How the two explanations articulate

In the following, we argue that the second explanation subsumes the first one. As a first step, we document that higher intangible investments are associated with lower business effectiveness, while the decrease in business effectiveness is not limited to firms with high intangible investments. As a second step, we show that controlling for intangible intensity explains only a small part of the trend in EQ, while controlling for business effectiveness explains the majority of it.

From an econometric perspective, the conclusion of Srivastava (2014) is debatable because it does not appropriately consider the mechanism of change associated with the progressive decrease in cross-sectional business effectiveness over the last four decades. The only variable somewhat related to this mechanism of change in his analysis, revenue volatility, does not capture the increase in the economic riskiness of firms.[4] In the sample we analyze, the correlation of volatility of cash flows to that of revenues is only 19%. By not considering proxies for firm characteristics whose development is associated with the decline in EQ measures (i.e., profitability, operational efficiency, and economic risk) and by choosing an explanatory variable that is correlated with these (*SG&A* intensity), the analysis in Srivastava (2014) yields biased inferences. We present formal evidence

[4]While Srivastava (2014) documents a steady increase in the cash flow volatility for successive cohorts, fails to include it among the possible explanatory factors of the EQ evolution.

supporting this claim in Section 6 .

3 . Methodological aspects

To disentangle the relevance of different mechanisms of change to the evolution of EQ measures, we emphasize a firm-year approach that contrasts with the cross-sectional perspective in the analysis by Srivastava (2014). In this section, we present the main components of this firm-year statistical perspective. We redefine two of the EQ measures (sections 3 .1 and 3 .2) and discuss the concrete details of the statistical estimation and testing (sections 3 .3 and 3 .4) to prepare the presentation of the empirical analysis in Sections 6 and 7 .

In the analysis we revisited, two of the EQ measures, matching and earnings relevance, were cross-sectionally constant. In other words, all firms in a given cross section (or cohort of a cross section) had the same value regarding matching or earnings relevance measures. As such, the two constructs cannot be used in a multivariate regression analysis that investigates the explanatory power of competing firm-specific variables (variables that take different firm-specific values) and need to be redefined. The alternative idiosyncratic firm-year EQ measures can be subjected to a multivariate regression analysis considering the two competing narratives contemporaneously, in this way addressing the issue of omitted variable bias arising in the univariate analyses that look at one narrative at a time.

3 .1. An alternative to earnings relevance

Srivastava (2014) uses the adjusted R^2 of the cross-sectional regression of annual stock returns on the levels of and changes in annual earnings as a measure of the relevance of earnings to prices. This section discusses an alternative firm-specific measure defined according to the framework of the EFP research design introduced in Starica and Marton (2020), which we briefly review in this section. Section A.1 in the Appendix gives the motivation for the design. For more details, see the above cited reference.

The alternative research design non-linearly regresses prices on earnings controlling for the factors that condition the price earnings relationship: firm's risk, growth profile, and accounting determinants (for example, unconditional conservatism). The non-linear regression guarantees an unbiased estimation of the economic relation between prices and earnings. The controls guarantee that firms with similar determinants of the price-earnings association have a similar estimated economic relation. Hence, for the firms in a cross section t, we estimate[5] the following empirical specification:

$$P_{i,t} := \mathbf{m}_t(NI_{i,t};\, r_{i,t},\, g_{i,t},\, ACC_{i,t}) + \varepsilon_{i,t}, \tag{1}$$

where where $r_{i,t}$ stands for a firm's risk, g_i denotes its growth, and C_i a measure of its accounting determinants. We discuss the proxies for risk, growth, and accounting determinants in Section 4 .1.

Firm-specific measure of association. Since the regression function in (1) can be interpreted as a valuation, the size of the estimated regression error

$$|\widehat{\varepsilon}_{i,t}| = |P_{i,t} - \widehat{\mathbf{m}}_t|$$

quantifies the extent to which future earnings expectations are shaped by information other than the level of earnings. For a given pair (i,t), we define the absolute relative valuation error to be the firm-year-specific measure of association (EFP) for the data

[5] We apply a non-parametric approach to non-linear regression estimation that is widely used in the machine learning and artificial intelligence applications (see Section 4 .1 for details).

entry (i,t):

$$EFP_{i,t} := \left|\frac{\widehat{\varepsilon}_{i,t}}{P_{i,t}}\right| = \left|\frac{P_{i,t}-\widehat{\mathbf{m}}_t}{P_{i,t}}\right|. \tag{2}$$

This amounts to the proportion of the price corresponding to earnings expectations shaped by information other than the current value of earnings.

An example. This research design is particularly useful when investigating whether or not the association of earnings with prices depends on a given firm characteristic. An example of such a research question is: "Are earnings of firms in earlier cohorts more relevant to investors price setting than those of firms listed later?" In the outlined EFP framework, the researcher first estimates cross-sectionally the non-linear regression (1). Then, she splits the sample conditional on the level of the firm's characteristic (in the case of the example, into competing subsets of earlier-listed and more recently-listed firms) and tests for differences in the median size of the absolute pricing error (2) calculated on the sub-samples. She interprets statistically significant differences as evidence of the impact of the given firm characteristic on earnings pertinence to the expectation formation process. In our example, if firms in earlier cohorts command higher valuation accuracy than those in later ones, we answer the research question positively.

3 .2. An alternative to Srivastava (2014)'s matching measure

Srivastava (2014) measures the matching of revenues and expenses using the $b_{3,t}$ coefficient in the following regression inferred on an annual cross-sectional basis:

$$Revenues_{i,t} = b_{1,t} + b_{2,t}\ Total\ Expenses_{i,t-1} + b_{3,t}\ Total\ Expenses_{i,t}$$
$$+ b_{4,t}\ Total\ Expenses_{i,t+1} + \varepsilon_{i,t}.$$

The coefficient $b_{3,t}$ mainly captures the contemporaneous cross-sectional correlation between revenues and expenses. As an earnings relevance measure, Srivastava (2014)'s matching construct $b_{3,t}$ is also cross-sectionally constant and hence ill-suited for a multivariate regression analysis that investigates the explanatory power of competing firm-specific variables. To address this issue, we measure matching based on the firm-year-specific correlation between contemporaneous revenues and total expenses (scaled by the average of the beginning and end of the total annual assets), $cor(Revenues_{i,t}, Expenses_{i,t})$, estimated based on recent firm data.

3 .3. *Changes in EQ measures over time – the cohort story*

To analyze the changes in EQ measures over time[6] and to determine which firm characteristics are associated with these dynamics, we use two types of conditional means.

I. Construct for testing the "new-listing" effect. To evaluate the impact of cohort membership on EQ measures and statistically test the "new-listing" effect, we compare the yearly mean EQ measures conditional on belonging to cohort Co:

$$\mathbb{E}[EQ_t \,|\, Co]. \tag{3}$$

More specifically, for two given cohorts i and j, cohort membership at year t is associated with differences in the level of the EQ measures if

$$\mathbb{E}[EQ_t \,|\, Co_i] \neq \mathbb{E}[EQ_t \,|\, Co_j].$$

II. Construct for testing cross-sectional association. To determine whether or not the dynamics of a firm characteristic Ch matches the evolution of the EQ measures, we use the yearly mean EQ measure conditional on both membership in cohort Co and the level

[6]This section is particularly relevant to the dynamic analysis in Section 6 .2.

of firm characteristic Ch at time t:

$$\mathbb{E}[EQ_t \,|\, Co, Ch_t] \tag{4}$$

We conclude that this is the case if controlling for the level of the characteristic Ch eliminates (or substantially reduces) the differences between the conditional cohort means:

$$\mathbb{E}[EQ_t \,|\, Co_i, Ch_t] \approx \mathbb{E}[EQ_t \,|\, Co_j, Ch_t].$$

3 .3.1. Estimation of the two conditional means

To infer the first construct $\mathbb{E}[\mathrm{EQ}_t \,|\, Co]$, which is the mean EQ (at time t) conditional on membership in cohort Co, we estimate the following unbalanced time-fixed effect panel linear model on a three-year moving window centered at year t:

$$EQ_{i,u} = \mu(t) + \beta_1(t) D_{i,u}^{(Co_1)} + \beta_2(t) D_{i,u}^{(Co_2)} + \ldots + \beta_m(t) D_{i,u}^{(Co_m)} + \varepsilon_{i,u}, \tag{5}$$

where $u \in \{t-1,\ t,\ t+1\}$ and $D^{(Co_j)}$ are the dummy variables 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 a reference.

The parameters in expression (5) have intuitive interpretations:

$$\begin{aligned} &\mu(t) = \mathbb{E}[EQ_t \,|\, Co_0], \\ &\beta_j(t) = \mathbb{E}[EQ_t \,|\, Co_j] - \mathbb{E}[EQ_t \,|\, Co_0], \quad j \in \{1, 2, \ldots, m\}. \end{aligned}$$

In other words, $\mu(t)$ is the mean EQ of the reference cohort 0 in year t, 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 year t. Coefficients $\beta_j(t)$ strictly greater than 0 provide evidence of lower mean EQ for firms in cohort j with respect to the reference cohort (in year t) and vice versa. That is, these provide evidence of the "new-listing" effect.

To estimate the second construct $\mathbb{E}[EQ_t \,|\, Co, Ch_t]$, which is the mean EQ (at time t) conditional on belonging to cohort Co and on the level of firm characteristic Ch, we add the characteristic Ch to control for the explanatory variables in equation (5), yielding the following regression:

$$EQ_{i,u} = \mu(t) + \beta_1(t) D_{i,u}^{(Co_1)} + \ldots + \beta_m(t) D_{i,u}^{(Co_m)} + \gamma(t) Ch_{i,u} + \varepsilon_{i,u}, \tag{6}$$

where $u \in \{t-1,\ t,\ t+1\}$ and Ch stand for *SG&A* intensity and profitability, efficiency or economic risk, respectively.

The parameters in (6) can be easily interpreted:

$$\mu(t) = \mathbb{E}[EQ_t \,|\, Co_0,\ Ch_t],$$

$$\beta_j(t) = \mathbb{E}[EQ_t \,|\, Co_j,\ Ch_t] - \mathbb{E}[EQ_t \,|\, Co_0,\ Ch_t], \quad j \in \{1, 2, \ldots, m\}.$$

In other words, $\mu(t)$ is the mean EQ of firms in the reference cohort 0 in year t (keeping the level of the characteristic Ch_t constant), while $\beta_j(t)$ is the incremental change[7] in the mean EQ of firms belonging to cohort j (over the mean EQ in the reference cohort; keeping the level of the firm characteristic Ch constant). Coefficients $\beta_j(t)$ strictly greater or smaller than 0 provide evidence of a lower or higher mean EQ for firms in cohort j, respectively, with respect to the reference cohort (in the year t) when keeping the level of the firm characteristic Ch constant. In other words, this can provide evidence against an association between changes in EQ measures with the evolution of the characteristic Ch.

[7]It is well known that when the independent variable in a linear regression is an indicator variable, testing the null hypothesis of a 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)).

3 .4. *Statistical hypothesis testing setup*

In the following analysis, the reference cohort will be that of seasoned firms, that is, firms that were listed before 1970. Formally, for a given year t we perform the following hypothesis test:

$$\begin{aligned} H_0: &\quad \beta_j(t) = 0 \\ &\text{vs.} \\ H_1: &\quad \beta_j(t) > 0 \quad (\beta_j(t) < 0), \end{aligned} \tag{7}$$

with $j \in \{1,2,\ldots,m\}$. The test is performed by constructing a 95% one-sided confidence interval for the coefficient $\beta_j(t)$, which we display around $\beta_j(t)$, and verifying whether or not 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,

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

or

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

we conclude that the average EQ measure in the later cohort j is higher (or lower) than that of the seasoned firms.

3 .5. *Presentation of statistical results: graphs vs tables*

As the year t moves incrementally through the cross-sections in the sample (from $t = 1970$ to $t = 2016$), the estimation of the regressions (5) and (6) yields yearly point estimates $\beta_j(t),\ j = 1,2,\ldots,m$, as well as yearly standard errors (SE) $SE(\beta_j(t)),\ j = 1,2,\ldots,m = 4$. Tabulating these estimates would require cumbersome tables with 47 lines and 8 columns. Besides the sheer amount of space required (our analysis would produce 9 such tables), tabulating such a large number of statistical outputs makes the interpretation of results difficult.

A better alternative (both in terms of space and readability) is to graphically display the point estimates and their standard errors as curves. More precisely, the point estimates are displayed as $m = 4$ functions of time

$$t \to \beta_j(t), \quad t = 1970, 1971, \ldots, 2016, \quad j = 1, 2, 3, 4$$

that 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 graphs display also (as functions of t) the m one-sided 95% confidence intervals

$$t \to \beta_j(t) \pm 1.65 * SE(\beta_j(t)), \quad t = 1970, 1971, \ldots, 2016, \quad j = 1, 2, 3, 4.$$

Note that, in the graphical presentation of statistical results, the standard errors of the point estimates is reported by the width of the confidence interval. This choice of reporting the SE is advantageous as it greatly facilitates the formal testing the hypothesis of interest: "the average EQ measure in later cohort j is higher than that of the seasoned firms". If 0 belongs to the confidence interval, than the hypothesis is rejected, otherwise it is accepted.

We emphasize that the information contain in a table tabulating the point estimates and their SE is identical to that presented in a graph displaying the time evolution of the point estimates and their confidence intervals as functions of time (curves). The graphical presentation saves space and facilitates the interpretation of the statistical analysis. For these reasons, the results of the empirical analysis in Section 6 .2 will be presented in the form of graphs displaying the m curves of point estimates together with the m one-sided 95% confidence intervals for hypothesis testing.

4 . Variable definitions, sample, and cohort construction

The following definitions are needed before we discuss the key variables for the empirical analysis. In line with Srivastava (2014), we define accruals (TACC) as changes in current assets (ACT) minus changes in cash (CHE) minus change in current liabilities (LCT) minus change in tax payable (TXP) minus depreciation and amortization (DP) and scaled by average total assets (Compustat AT) for the year. Up to 1988, cash flow from operations (CFO) is defined as the difference between earnings (Compustat IB) and accruals. To address the fact that balance sheet-based accruals might be affected by measurement errors (Hribar and Collins, 2002), we use CFO as disclosed in statements of cash flows for years after 1989.

4 .1. Key variable definitions

Earnings qualities. Following Srivastava (2014), we focus on three EQ measures: earnings volatility, matching of revenues and expenses, and the pertinence of earnings to prices.

Earnings volatility. Following Givoly and Hayn (2000) and Dichev and Tang (2009), we scale earnings (Compustat IB) by the average of the beginning and end of the annual total assets and estimate their standard deviation for each firm year using at least four values[8] from the eight most recent annual observations ($t-7$ through t).

Matching. As explained in Section 3 .2, we measure matching based on the correlation between contemporaneous revenues and total expenses scaled by the average of the beginning and end of the annual total assets $cor(Revenues, Expenses)$. we compute total expenses by subtracting income before extraordinary items (Compustat IB) from rev-

[8]The sample contains firm years with available data for at least four of the eight most recent years.

enues (Compustat *SALES*) (Dichev and Tang, 2009; Srivastava, 2014). We estimate this correlation for each firm year (i,t) using the available pairs[9] $(Revenues, Expenses)_{i,t-s}$, $s = 1, 2, \ldots, 8$ among the eight most recent annual observations ($t-7$ through t).

Earnings expectation formation pertinence. Starica and Marton (2020) investigate the optimal choice of proxies for firm risk, growth, and accounting determinants in the valuation regression (1). Their results support a parsimonious choice of three proxies that are responsible for most of the explanatory power of the valuation regression: P/B ratio, market size ($Mktv$), and leverage (Lev). On each cross section t, we infer the valuation regression

$$P_{i,t} := \mathbf{m}_t(IB_{i,t};\ (P/B)_{i,t},\ Mktv_{i,t-1},\ Lev_{i,t}) + \varepsilon_{i,t}.$$

and construct the absolute relative valuation error defined in (2), our measure of the EFP of earnings. We use Compustat IB as a measure of net income, the share price three months after the end of the fiscal year as P, and Compustat CEQ for the book value of equity B. $Mktv$ is the product of the stock price P with the number of common shares outstanding (Compustat CSHO), while the Lev is defined as the ratio of long term debt (Compustat LT) to market value.

The results we report were obtained using the random forest (RF) approach to non-parametric non-linear regression estimation. For a firm i, the RF method approximates the function to estimate $\mathbf{m}$ based on a local average of the prices of entities with explanatory variables close in value to those of the firm i. As such, the valuation in which the expectations of future abnormal earnings are informed only by the level of earnings of the firm i is a local average of prices of firms that have similar levels of earnings, risk, growth, and

[9] By construction of the sample, at least four of these values are not missing.

accounting conservatism (as proxied by size, P/B ratio, and Lev).

Intangible expenditures. We define two complementary measures of intangible investments: an intensity measure and a relative measure.

SG&A intensity. Following Srivastava (2014), we measure the $SG\&A$ expenses by the Compustat data item $XSGA$ and define the $SG\&A$ intensity ($S\&GAi$) as the proportion of $SG\&A$ expenses represented in the firm year's total expenses, that is, as the ratio between $XSGA$ and total expenses.[10]

R&D investments. A common measure of the level of intangible assets in a firm is the ratio of R&D expenditures (Compustat XRD) to assets. Kahle and Stulz (2017) documents a steady increase in the proportion of firms' total assets represented by R&D investments from approximately 1% in 1975 to approximately 6% in 2015. Around 2001, the proportion of total assets represented by R&D expenditures exceeded that of capital expenditures, and the gap has grown further in recent years.

Business effectiveness. We also consider the following measures of profitability, operational efficiency, and economic risk that we will use to assess the business effectiveness of firms.

Profitability. One well-accepted measure of profitability is the ratio of a firm's operating cash flow to its revenues ($CFO/SALES$). This ratio reveals the ability of a business to generate cash flow in proportion to its sales. As such, it is a relevant measures of the overall success of a firm, especially when combined with an evaluation of how well it is using its assets. An intriguing question regarding the deterioration in reported EQ is whether

[10] In our robustness checks, we use refinements of $SG\&A$ intensity as well as other measures of intangible expenditure (see, e.g., Brown and Kimbrough, 2011; Eisfeldt and Papanikolaou, 2013; Enache and Srivastava, 2018, as well as section A.3), as alternatives to $SG\&A$ intensity.

it is a reflection of a real drop in the economic performance of companies or whether it is accounting-driven. To reduce this uncertainty, we prefer a profitability ratio based on CFO, a measure of individual company performance that is mostly unaffected by accrual accounting. In our robustness tests, other profitability measures (ROE, ROA, $IB/SALES$, and CFO/AT) gave qualitatively similar results (see Section A.4 in the Appendix).

Operational efficiency. The asset utilization ratio measures the efficiency with which a company is using its assets to generate revenues and is defined as the ratio of revenues to total assets ($SALES/AT$). We calculate the median asset turnover for each firm year using the eight most recent available annual observations ($t-7$ through t) of a firm's ratio of sales to total assets. Lower values of asset turnover for more recent cohorts indicate a decreased efficiency in generating sales.

Economic risk. Following the extant literature (Givoly and Hayn, 2000; Brown and Kapadia, 2007; Dichev and Tang, 2009; Irvine and Pontiff, 2009), we use the volatility of CFO as a measure of economic risk. We scale CFO by the average of the beginning and end of the annual total assets and estimate the standard deviations of these variables for each firm year using at least four of the eight most recent annual observations ($t-7$ through t).

4 .2. How lower business effectiveness causes lower EQ measures

This section explains the mechanisms through which lower business effectiveness manifests into lower EQ measures. Empirical evidence of the positive association between business effectiveness and EQ measures is presented in section 6 .1.

A direct relation exists between higher economic risk and higher earnings variability as firms with higher economic risk, that is, more volatile cash flows, tend to have more volatile earnings (Lang et al., 2006; Barth et al., 2008). Volatile cash flows also make earnings more difficult to forecast (Dichev and Tang, 2009). Consequently, the relevance of earnings numbers to the price formation decreases.

High levels of CFO/AT often indicate that a higher proportion of value creation in the firm is related to short-term flows rather than created by long-term assets. This implies lower importance of long-term accruals, e.g., depreciation and amortization, whose estimation involves often large errors, and therefore higher-quality accruals. Earnings with high-quality accrual component have higher pertinence for stock prices.

Another argument for the positive relation between our profitability variable and the EFP quality measure is based on the findings in Sloan (1996). Since stock prices act as if investors correctly anticipate the persistence of the cash flow component while failing to anticipate the lower persistence of the accruals, the level of profitability variable (CFO/AT) has a direct impact on the price formation (the analysis in the cited paper and related research scales all variables by the total assets, that is, their cash flow variable corresponds to our profitability). As such, high levels of CFO/AT are associated with more precise pricing. Lower pricing error means lower EFP values.

Intuitively, higher revenues ($SALES/AT$) should facilitate covering of expenses improving matching. Also, as alreay mentioned, higher economic risk leads often to higher earnings volatility which, by the definition of expenses, results in higher volatility of the later. Everything else constant, more variable expenses worsens matching, since $cor(Revenues, Expenses)$ is invers proportional to the volatility of expenses. Alternatively, one can argue that smooth cash flow streams, most likely, facilitates estimation of accruals, hence reducing their volatility.[11] As most accruals are related to expenses,

[11] The volatility of the estimation error adds to the volatility of the true accruals to produce the volatility of estimated accruals.

stable cash flow streams result, everything else constant, in less volatile expenses. Lower standard deviation for expenses implies higher matching, since $cor(Revenues, Expenses)$ is invers proportional to the volatility of expenses.

The following argument converts some of these intuitions into an analytic proof. The impact of lower business effectiveness variables, in particular that of lower efficiency and higher economic risk, on matching is more subtle and is made clear by the following analytic derivation. Let us make the following definition:

$$u =: \frac{cov(SALES/AT,\ IB/AT)}{Var(SALES/AT)}.$$

Note that if the sales increase (for example, by a factor of 2), u decreases (by same factor):

$$\frac{cov(2 \times SALES/AT,\ IB/AT)}{Var(2 \times SALES/AT)} = \frac{1}{2} \times \frac{cov(SALES/AT,\ IB/AT)}{Var(SALES/AT)}.$$

With the above notation the matching measure can be expressed as:

$$\begin{aligned} cor(Revenues, Expenses) &= cor(SALES/AT, (SALES - IB)/AT) \\ &= \frac{1-u}{\sqrt{1-u+Var(IB/AT)/Var(SALES/AT)}} \end{aligned}$$

The $cor(Revenues, Expenses)$ is a decreasing function of u (the higher the u, the lower the correlation). Putting together the two observations, we have that lower effciency $(SALES/AT)$ corresponds to higher u, which implies lower $cor(Revenues, Expenses)$.

The expression above establishes also the causal relation between higher economic risk and the matching of revenues and expenses. Everything else constant, higher economic risk implies higher earnings volatility, that is higher $Var(IB/AT)$. A larger denominator in the above fraction implies lower $cor(Revenues, Expenses)$. To conclude, lower operational efficiency and higher volatility of cash flows makes matching of revenues and expenses a more challenging task for the entreprise.

4 .3. Cohort definition

Following Srivastava (2014), we classify the firms in the sample into five cohorts. The reference cohort Co_0, ($j = 0$) is made up of firms that entered the database before 1970. The other cohorts begin at regular 10-year intervals and contain the firms that are listed during the 10 years after the first year. This yields four more cohorts: $Co_1 = 1970 - 1979$ ($j = 1$), $Co_2 = 1980 - 1989$ ($j = 2$), $Co_3 = 1990 - 1999$ ($j = 3$), and $Co_4 = 2000 - 2009$ ($j = 4$). We begin following each of the cohorts 10 years after its inception. This gives us 47 years of follow-up for the reference cohort, 37 for the first cohort, 27 for the second, 17 for the third, and 7 for the fourth.

4 .4. Sample

We use 223,649 firm year observations with valid data from the years 1962 through 2016. Following Srivastava (2014), we exclude all finance firms because the traditional cost classifications (i.e., cost of goods sold [COGS] vs. SG&A) do not apply to these firms. The yearly sample size is displayed in Figure A.1 in the Appendix. The first year in which a firm's data are available in Compustat is referred to as the "listing year." All of the firms listed in a common decade are referred to as a "cohort" of new firms. Figure A.1 also displays the time evolution of the size of the five cohorts under discussion. For calculating volatilities and correlations, we require that the firm year has at least four non-missing values within the eight most recent years.

Table 1 displays the summary statistics of the EQ measures (Panel A) and the explanatory firm characteristics (Panel B). The variables are winsorized at the 1% level.

Variable	Mean	SD	10%	25%	50%	75%	90%
Panel A: *EQ* measures							
$\sigma(NI)$	0.09	0.12	0.01	0.02	0.04	0.10	0.21
$\rho(Rev, Exp)$	0.91	0.18	0.72	0.91	0.98	0.99	1.00
EFP	0.57	0.91	0.05	0.13	0.28	0.57	1.34
Panel B: Firm's explanatory characteristics							
*SG&A*i	0.27	0.18	0.08	0.14	0.23	0.36	0.52
$CFO/SALES$	0.02	0.56	-0.04	0.02	0.05	0.11	0.19
$SALES/AT$	1.26	0.75	0.39	0.75	1.18	1.63	2.18
$\sigma(CFO)$	0.09	0.08	0.02	0.04	0.06	0.10	0.17

Table 1: **Descriptive statistics.** *Panel A: EQ* measures. *Panel B:* Firm characteristics.

Table 2 displays the values of Spearman (upper triangle) and Pearson (lower triangle) correlation between the regression variables (EQ measures and explanatory firm characteristics). The correlation between the EQ measures and firm characteristics as well as between the *SG&A* intensity and business effectiveness variables had the expected signs.

	$\sigma(NI)$	$\rho(Rev, Exp)$	EFP	*SG&A*i	$CFO/SALES$	$SALES/AT$	$\sigma(CFO)$
$\sigma(NI)$	1.00	-0.56	0.37	0.29	-0.35	-0.09	0.61
$\rho(Rev, Exp)$	-0.39	1.00	-0.26	-0.28	0.00	0.44	-0.18
EFP	0.29	-0.21	1.00	0.10	-0.16	-0.13	0.23
*SG&A*i	0.33	-0.25	0.13	1.00	-0.16	-0.23	0.23
$CFO/SALES$	-0.07	0.06	-0.03	-0.07	1.00	-0.28	-0.45
$SALES/AT$	-0.10	0.32	-0.10	-0.26	0.04	1.00	0.13
$\sigma(CFO)$	0.70	-0.27	0.24	0.32	-0.07	-0.03	1.00

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.

5 . Making our case

This section develops our narrative with heuristic evidence, while the next section puts forward formal statistical support for the heuristic discussion. We believe it is important to discuss in depth the intuition behind our explanation and how our findings cohere with the results in the previous literature before going into a rigorous quantitative analysis where a large number of hypothesis are formally tested.

There are three main points we are trying to make in this section. First, we argue that the evolution of *SG&A* intensity cannot explain the decrease in *EQ* measures. While the former mainly affects industries with high intangible expenditure levels, the latter is an economy-wide phenomenon. At the same time, the evolution pattern of *EQ* measures is similar to that of the business effectiveness variables.

Second, we corroborate that the business effectiveness variables subsume the *SG&A* intensity. A direct consequence of the change in the development trend of the U.S. financial sector leading to the revival of the financial markets in the 1970s is that weaker firms and firms with more distant expected payoffs become able to issue public equity. We present new evidence supporting this evolution and give a nuanced picture of its development. While some of the newcomers to the market were both weaker and had high intangible intensity, the decrease in business effectiveness affected all industries, independent of their level of intangible expenditure. Even the newcomers operating in industries with low intangible investment (which are in fact the majority of new arrivals) are getting successively weaker. Their decline in effectiveness has no relation to higher intangible investments. As such, while possibly accentuated by higher intangible intensity, the decrease in business effectiveness does not seem to be caused by it.

Third, we explain how we can reconcile our claim that relates the evolution of *EQ* to financial development with the association between the evolution of intangible investment and *EQ* measures put forwards in the previous literature. We argue that the association is the result of an analysis affected by an omitted variable bias and a direct consequence of the fact that the business effectiveness variables subsume the *SG&A* intensity. If the generalized decrease in the business effectiveness of public firms is driving the evolution of successive cohorts towards lower levels of EQ, since higher intangible investment levels are associated with lower business effectiveness (even if only for a part of the economy), an analysis that takes into account the former but not the latter would find a significant association between higher levels of intangible investment and lower EQ measures by virtue of the omitted variable bias. However, once the business effectiveness variables become part of the analysis, the coefficients of the correlated variable (intangible investment) lose their significance, the bias is corrected, and the link between business effectiveness variables and EQ measures remains the only significant association. While this section attempts to convince the reader that this is the case based on heuristic arguments, Section 6 puts forward a rigorous proof of our omitted variable bias narrative.

5 .1. SG&A intensity evolution does not fully explain decreasing EQ measures

In this section, we argue that higher *SG&A* intensity is associated with lower EQ values only for a subset of the firms in the newer cohorts. For most of the new arrivals, their lower business effectiveness is not matched by augmented intangible expenditures. This partial pattern of association does not match the structure of the economy-encompassing decline in EQ measures evident in the data. Our evidence suggests that changes other than the increase in intangible investment must be at the root of the economy-wide decrease in EQ measures.

5 .1.1. The evolution patterns of intangible investments and EQ do not match

Intangible investments. Srivastava (2014) puts forward evidence that "each successive wave exhibits higher SG&A intensity than its predecessor," with one exception: he does not find a significant difference between the waves in the 1980s and 1990s. The graphs in Figure 1 reveal a more nuanced picture. These display, in order, the evolution of cohorts' mean *SG&A* intensity and *R&D* investment for (a) the whole economy; (b) the hi-tech and healthcare, medical equipment, and drugs industries (industries 3 and 4 in the Fama French 5 industry classification); and (c) the rest of the industries (industries 1, 2, and 5 in the Fama French 5 industry classification). To produce the graphs in this figure (as well as all graphs illustrating the evolution of cohorts' means), we calculate and display the median value of each variable of interest (here, the *SG&A* intensityand *R&D* investments) conditional on the cohort and year. The conditional median is calculated based on a moving window of size three. This yields five curves describing the change over time of the cohort-specific average.

Before we comment on this in detail, let us state the main takeaway of Figure 1. Namely, the figure shows that the successive increase in intangible investments (as measured by the *SG&A* intensity and *R&D*) affects only part of the economy, while most of it[12] shows little, if any, difference between successive cohorts. In other words, the successive increase in intangible investments noticeable in the left-hand column of the figure is due overwhelmingly to evolution in the high-tech and healthcare, medical equipment, and drugs industries.

A close look at the graphs in Figure 1 reveals a number of important details. First, a difference is noticeable between the mean *SG&A* intensity levels of the waves in the 1980s and 1990s (non-existent in the analysis of Srivastava (2014)). In fact, this is the largest inter-cohort difference. More importantly, the 2010 cohort, which is not present in Srivastava (2014)'s analysis, shows an inversion of this trend. Contrary to the trend of the previous cohorts (and in opposition to the upward trend in the *EQ* measures shown

[12] At least 55% of the firms in the economy in any of the cross sections belonged to low intangible intensity industries. Moreover, with the exception of a few years around the year 2000, the market value of low intangible intensity firms represented more than 50% of the total market value in most of the cross sections. See also Figure 2.

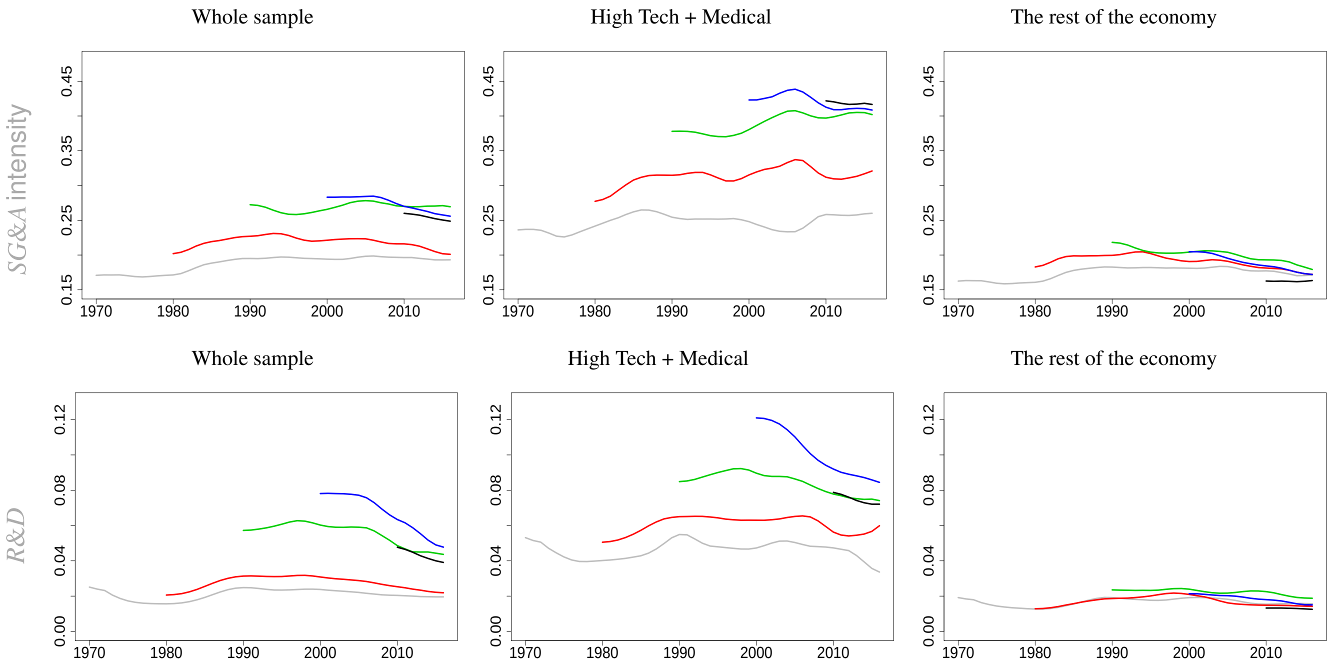

Figure 1: **Evolution of intangible investment measures.** The plots display the cohorts' mean *SG&A* intensity (top) and *R&D* investment (bottom) smoothed over a three-year moving window as a function of time. The time points at which each of the curves begins indicate the cohorts represented by the curves. The graphs in the first column are based on the entire sample, those in the second on only the high intangible intensity industries (hi-tech and healthcare, medical equipment, and drugs; industries 3 and 4 in the Fama French 5 industry classification), while the graphs in the third column are based on the other industries (low intangible intensity industries). The successive increase in the intangible investment measures of newer cohorts affects mostly or only the high intangible intensity part of the economy.

in Figure 3), the mean intangible investment measures of the most recent cohort are at the level of the 1990 cohort. This inversion of the trend is due to a change in the level of intangible intensity in the high-tech and healthcare, medical equipment, and drugs industries. Since the evolution of the two intangible investment measures is similar and for the sake of comparability with the results in Srivastava (2014), in the following we use *SG&A* intensity as a measure of the level of intangible expenditures.

The decrease in the mean level of intangible investment is accompanied by a reduction in the proportion of firms active in industries with high intangible expenditures. Figure 2 displays the time evolution of the proportion of firms in such industries in the economy as a whole and in each of the cohorts. The evolution of the proportion of high intangible intensity firms in the cross section has a peak at 45% around the year 2000. The cohort

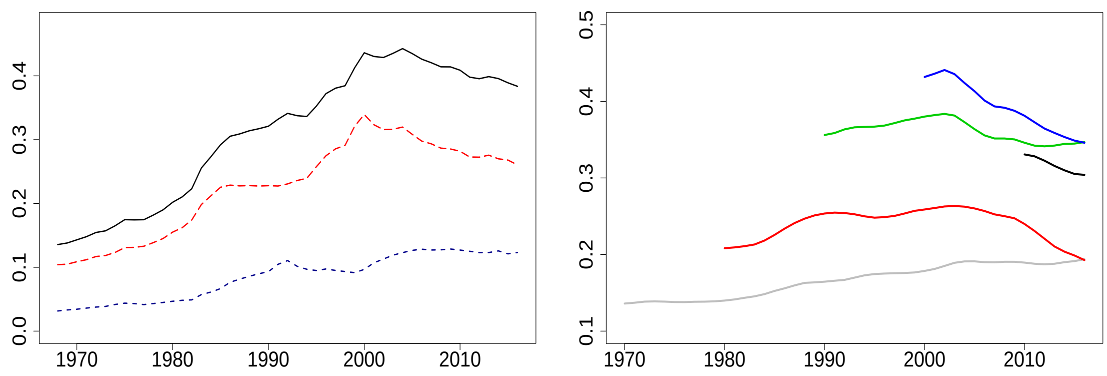

Figure 2: **Evolution of the proportion of firms in high intangible expenditure industries.** The graph on the left displays the evolution of the percentage of firms in 1. healthcare, medical equipment, and drugs (industry 4 in the Fama French 5 industry classification; bottom curve, blue, dotted), 2. hi-tech (industry 3 in the Fama French 5 industry classification; middle curve, red, dashed), and 3. high intangible intensity industries (the sum of the previous two curves; top curve, black, full). The graph on the right shows the evolution of the proportion of firms in intangible intensive industries in each of the five cohorts under discussion. We note an inversion of the trend towards lower percentages of high intangible intensity firms for the 2010 cohort.

evolution graph on the right side of the figure shows that, while up to the year 2000 the proportion of intangible intensity firms was augmented constantly with roughly 10% per cohort, the 2010 cohort shows a surprising inversion of this trend. From its inception, the 2010 cohort has proportionally fewer firms in high intangible investment industries than even the 1990 cohort.

These findings are consistent with the hypothesis of a new phase in the evolution of U.S. financial development characterized by a reduction in the importance of the exchanges for the U.S. economy, proposed recently in a series of papers (Doidge et al., 2017; Kahle and Stulz, 2017; Doidge et al., 2018). In particular, Doidge et al. (2018) suggestively describe this phenomenon as an "eclipse of the public markets as the place where young, successful, American companies seek their funding". The hypothesis, as phrased in Kahle and Stulz (2017), states that "participating in public markets is not as beneficial for firms that invest in intangibles as it is for firms that invest in fixed assets, especially when these firms are small and young." For the former, it is much more difficult to convince public investors that they will make good use of their money. In contrast, it is much easier for such firms to raise capital from private equity investors. The rise of private equity may be one of the contributing factors to the fact that fewer high intangible intensity firms have recently chosen to participate in the public markets (as shown by the graphs in Figure 2).

EQ measures. Figure 3 presents the time evolution of the mean EQ measures of consecutive cohorts from 1980 up to 2016 over the whole economy as well as separately for the high and low intangible intensity industries (as defined in the previous section).

Figure 3 confirms that the evolution of mean cohort EQ measures shows a pattern clearly fitting the "listing effect," as documented in Srivastava (2014), with the cohort means neatly separated from one another.[13] The variation of the EFP is more pronounced, with evident swings around the internet bubble and the 2008 financial crisis. Newer cohorts are characterized by higher earnings volatility, lower levels of matching between revenues and expenses, and lower relevance of earnings numbers to price formation.

However, the main takeaway from the graphs in Figure 3 is something different, namely, that the decline in EQ measures is manifest not only in the high intangible intensive industries but also throughout the rest of the economy.

The evolution of *SG&A* intensity cannot explain that of EQ measures. Two observations provide evidence against the explanation of decreasing EQ based on successive increases in *SG&A* intensity proposed in Srivastava (2014). First, the decrease in EQ measures is an economy-wide phenomenon (see Figure 3), while the successive increases in *SG&A* intensity is limited to only a part of the economy, representing roughly one-third

[13] Recall that we have redefined two of the EQ measures, matching and earnings relevance, to render them amenable to a multivariate analysis that controls for the levels of firm characteristics competing to explain their dynamic.

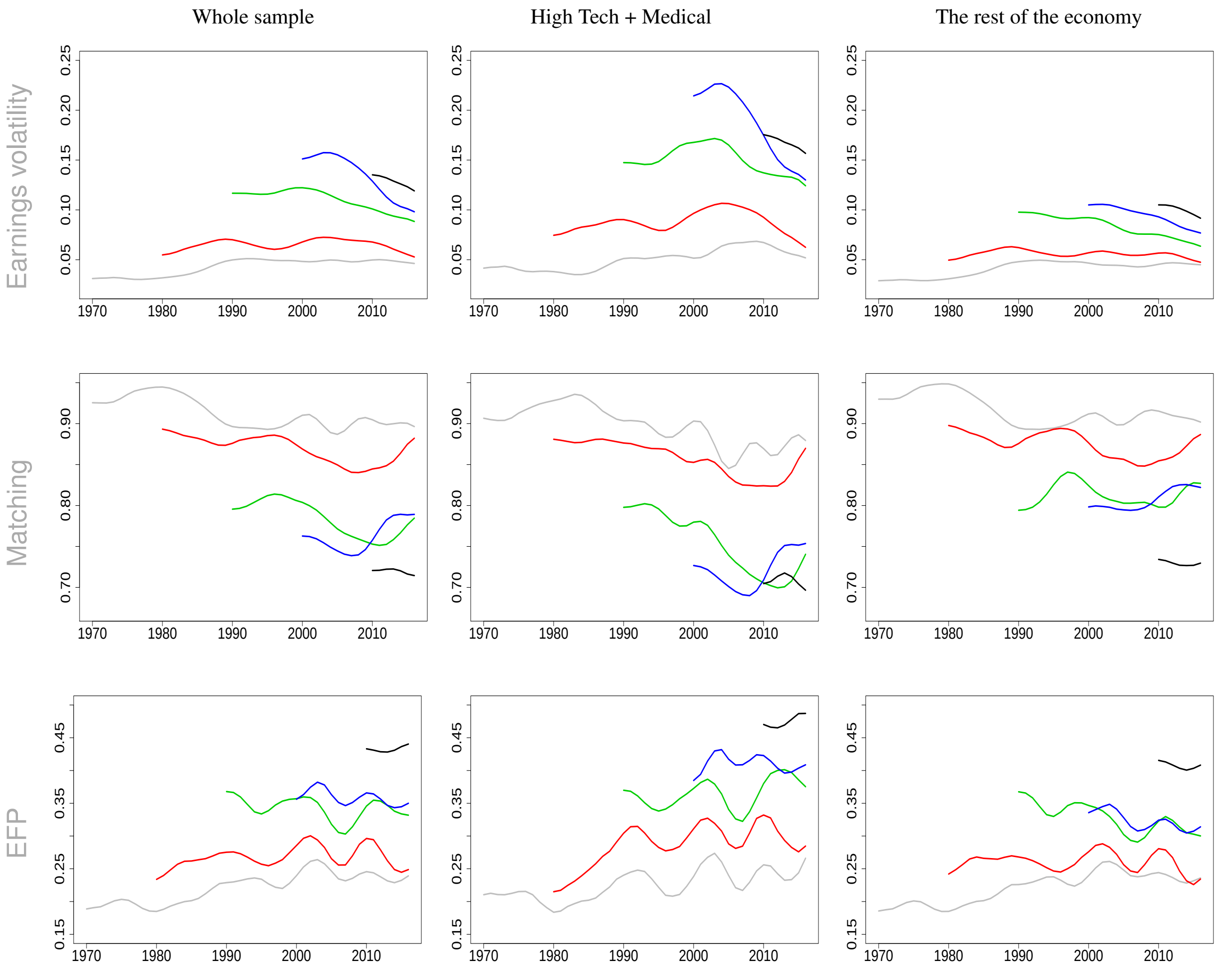

Figure 3: **Time evolution of EQ measures.** The plots display the means of the three EQ measures of the cohorts (smoothed with a three-year moving window) as a function of time. The variables are specified in the labels on the side of the graphs in the first column. The first column is based on the entire sample, the second one uses only the high intangible intensity industries (hi-tech and healthcare, medical equipment, and drugs; industries 3 and 4 in the Fama French 5 industry classification), while the graphs in the third column are based on the other industries (low intangible intensity industries). All three measures show evidence of the "listing effect." Unlike the evolution of *SG&A* intensity , which affects only the high intangible intensity industries (see Figure 1), the decay in EQ measures is an economy-wide phenomenon.

of the firm years in the sample (see Figure 1). The intangible intensity level of newer cohorts in industries other than the high-tech and medical industries, which account for at least half of the economy,[14] remains practically constant, while their EQ measures get progressively worse. Consequently, controlling for the level of firms' *SG&A* intensity cannot possibly explain the evolution of the EQ measures for firms in low intangible in-

[14]It is worth noticing that even when the proportion of high intangible intensity firms was at its apex, 55% of the firms in the economy belonged to low intangible intensity industries and that, with the exception of a few years around the year 2000, the market value of low intangible intensity firms has represented more than 50% of the total market value.

tensity industries. Second, while the last cohort shows lower *EQ* measures (left-hand side of Figure 3), its *SG&A* intensity is not higher than that of the previous cohort (top left graph in Figure 1). The change of trend in the level of *SG&A* intensity that affects the last cohort in Figure 1 is matched by similar patterns in other measures of intangible investment (see Figure A.3 in the Appendix).

5 .2. An economy-wide decrease in the business effectiveness of newer arrivals

In this section we present heuristic evidence of an economy-wide decrease in the profitability and efficiency of newer cohorts and of an increase in the economic risk of these cohorts. We document that higher levels of *SG&A* intensity are matched by lower business effectiveness, but that the reduction in the latter is not limited to the high-tech and medical industries but is manifest throughout the whole economy. The upward trend in financial development (beginning sometime in the 1970s) documented by Rajan and Zingales (2003) should imply for financial markets significant changes in the cross-sectional distribution of firm characteristics. As the access to financial markets becomes easier, and a greater fraction of the economy becomes publicly held, we should expect to see that the newcomers have deteriorating fundamental characteristics. This section looks at the relative performance of three fundamental characteristics of consecutive cohorts: profitability, operational efficiency, and economic risk.

Since all three ratios measuring business effectiveness vary significantly between industries, to make our argument regarding the overall decline in firm business fit more convincing, we analyze the evolution of cohort effectiveness within various industries.[15] More concretely, for a given cross section and a given industry,[16] we rank the firms in

[15]Using relative business fit measures avoids mistaking changes in cross-sections' industry composition for changes in business effectiveness.

[16]We use Fama French 48 industry classification in this analysis.

the industry based on each of the three ratios and use firms' within-industry ranks[17] as a relative measure of effectiveness. We then calculate and display the cohort's mean rank. A lower ranking of a cohort with respect to the others indicates a decay in business effectiveness.[18]

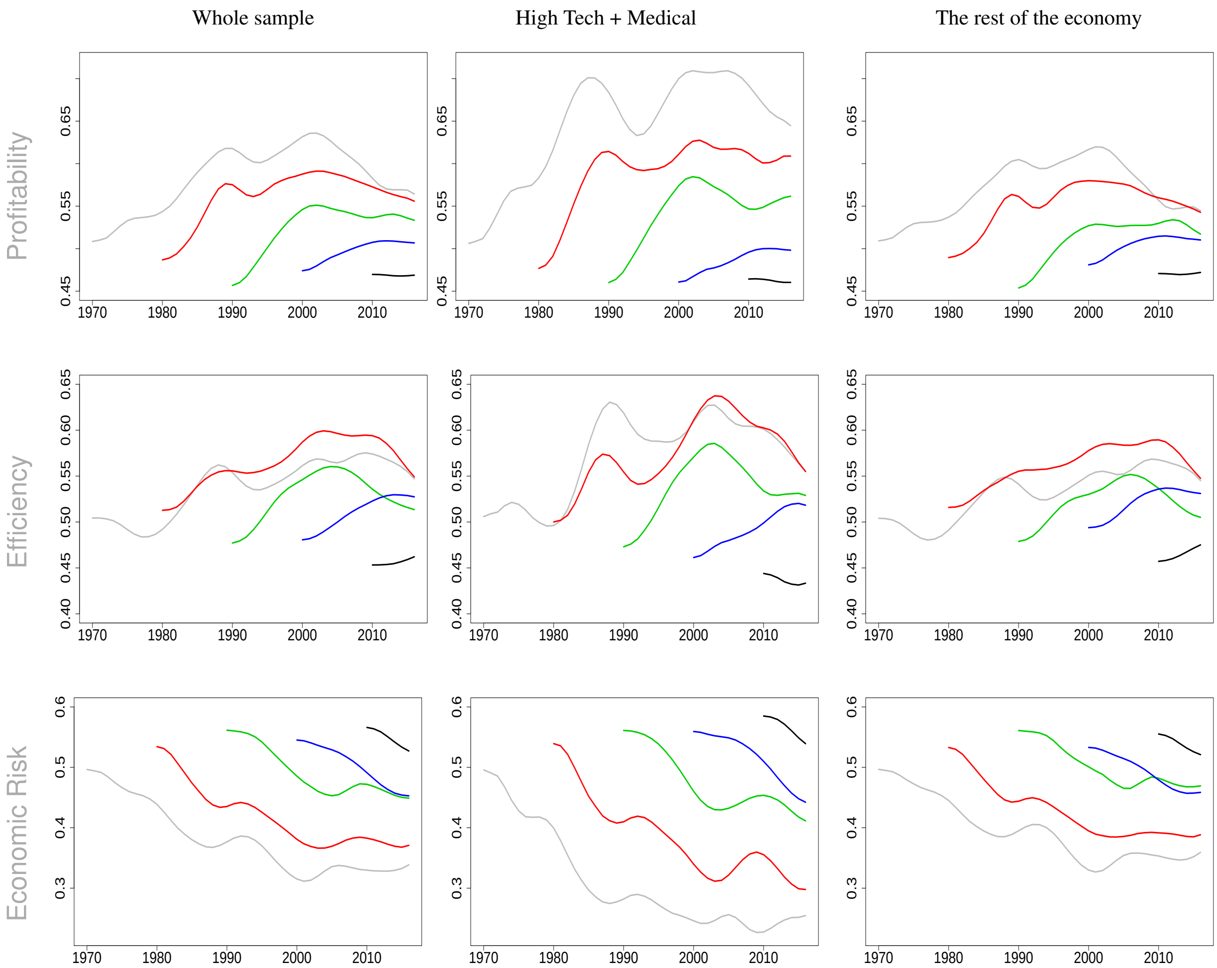

Figure 4: **Time evolution of firm characteristics measuring business effectiveness.** For a given cross section and for each industry we rank the firms in the industry based on the values of the business effectiveness variables under study and use a firm's rank within its industry (on a scale from 1 to 100) as a relative measure of effectiveness. The plots display cohorts' mean rank regarding firm business effectiveness characteristics (indicated in the title on the left-hand side of the figure) within the firms' industry (Fama French 48 industry classification). The means are smoothed over a three-year moving window. The graphs document an overall decline in business effectiveness variables, manifest in both low and high intangible intensity sectors of the economy.

The graphs in Figure 4 show the time evolution of the mean values of the ranks of

[17]We scale the rank on a 1 to 100 range.

[18]We conduct the rest of the analysis using the three ratios as values (and not their within-industry ranks) because the EQ measures are expressed in absolute terms and not relative to peers in the same industry.

the business effectiveness variables for consecutive cohorts. The graphs in the left-hand column are representative of the entire market, the central column represents only the high-tech and medical industries, and the right-hand graphs show the evolution for the rest of the industries in the economy.

The first takeaway from Figure 4 is that the business effectiveness variables subsume the *SG&A* intensity in the sense that higher levels of *SG&A* intensity are associated with lower business effectiveness while the reciprocal affirmation is not true. The graphs in the center column of Figure 4 present the evolution of the business effectiveness variables for the part of the economy that witnessed a consecutive increase in the *SG&A* intensity levels of newer cohorts (as documented by the graphs in the middle column in Figure 1). These show that higher levels of *SG&A* intensity are associated with lower firm business effectiveness (with the exception of the 2010 cohort, which has lower business effectiveness but not a higher *SG&A* intensity with respect to the previous cohorts). Firms with higher intangible intensity show lower profitability/efficiency and/or higher risk. Intuitively, *R&D*, advertising, and human capital spending that generate intangible assets are by nature associated with more uncertain outcomes in generating sales and positive cash flows, which might translate into lower profitability, efficiency, and/or higher economic risk.

However, the reciprocal is not true: lower successive levels of business effectiveness do not presuppose higher levels of intangible intensity. Industries with increasing intangible intensity are not the only ones that exhibit decreasing profitability, efficiency, and/or increasing risk. The graphs in the right-hand column of Figure 4 show that declining levels of business effectiveness are present in parts of the economy in which there is practically no evolution in cohorts' intangible investment level, that is, in industries other than the high-tech and medical industries. Despite no significant increase in intangible investment, the mean levels of business effectiveness variables decrease for consecutive cohorts (albeit with a lesser amplitude). Thus, higher intangible intensity does not seem to be equivalent to lower business effectiveness.

This finding is evidence that the explanation we propose in this study differs conceptually from Srivastava (2014)'s argument that increased intangible intensity accounts for the decline in EQ over time. Our explanation does not capture the same underlying phenomenon (the change in sample composition over time; newly-listed vs. existing) with the simple difference that we quantify the change in the sample using business effectiveness rather than intangible intensity. The evolution of business effectiveness is more ample than that of intangible intensity, and the decrease in business effectiveness subsumes the increase in intangible intensity.

The second takeaway from the graphs in Figure 4 is that the evolution of EQ measures and that of business effectiveness are similar, while the evolution of EQ measures and that of intangible investments are not. The progressive degradation of business effectiveness as well as that of EQ measures (for consecutive cohorts) are not limited to high intangible intensity firms but rather affect the whole economy. In contrast to this, the evolution of the level of intangible investments (as measured by *SG&A* intensity and the ratio of *R&D* expenditures to assets) is limited to the high-tech and medical industries (see Figure 1 and the discussion pertaining to it).

Consequently, while the increase in *SG&A* intensity cannot explain the degradation of EQ measures in low intangible intensity industries, the successive decrease in business effectiveness for newer cohorts may be able to do so, provided that lower business effectiveness is associated with lower EQ. In the next section, we turn our attention to precisely this issue, that is, the association between business effectiveness and EQ measures.

To summarize, we have seen that the evolution of cohorts' EQ measures as well as that of cohorts' business effectiveness are economy-wide phenomena, while the increase in *SG&A* intensity is limited to the high-tech and medical industries which contain less than half of the newly listed firms (in any cross section). We have also seen that lower business effectiveness and higher *SG&A* intensity are both associated with lower EQ measures, but that business effectiveness and *SG&A* intensity are not two faces of the same coin. Higher *SG&A* intensity implies lower business effectiveness, but the reciprocal does not hold. Despite no significant increase in the level of intangible investment, the mean business effectiveness of cohorts' firms in low intangible intensity industries decreases for successive cohorts. Higher intangible intensity is thus not equivalent to lower business effectiveness (Figure 4). The evolution of the business effectiveness variables subsumes that of the level of intangible investments.

5 .3. *Our narrative*

Two pieces of evidence point towards the fact that Srivastava (2014)'s narrative is, at best, only part of the story. First, the successive decrease in the EQ measures of newer cohorts is an economy-wide phenomenon (Figure 3), while the evolution of *SG&A* intensity towards ever higher levels is limited to high intangible intensity firms (Figure 1). Second, the 2010 cohort shows an inversion in the trend for *SG&A* intensity, while there is no change in the trend of EQ measures.

Putting together the evidence in Sections 5 .1 and 5 .2, our narrative regarding the evolution of EQ measures is as follows. As a result of a trend change in the state of development of the U.S. financial sector, which switched from negative to positive in the 1970s (Rajan and Zingales, 2003), progressively weaker firms have gained access to public financing. For some of these firms, the lower values of their business effectiveness proxies are associated with and possibly accentuated by high intangible expenditures. The decrease in the business effectiveness of this group of high intangible intensive firms, although comprising a minority of newcomers, is the most pronounced part of the evolution towards lower levels of business effectiveness in the newer cohorts (Figure 4, middle column).

However, for the majority of firms in the newer cohorts (75% in the 1980 cohort, 65% in the 1990 cohort, 60% in the 2000 cohort, and 70% in the 2010 cohort, Figure 2), the decrease in business effectiveness is not matched by significant changes in the level of intangible expenditures (Figure 1). These firms, operating in low intangible intensity industries, show progressively lower profitability and operational efficiency as well as higher economic risk. While slightly lower in amplitude, the decrease is significant (Figure 4, right-hand column). Because they are more numerous, they are the ones responsible for the pattern of decrease shown by the economy as a whole (the right and left columns of Figure 4 are rather similar). Overall, the economy-wide decrease in business effectiveness is shaped by the firms operating in industries with low levels of intangible expenditure.

The evolution of the cross-sectional structure along the dimension of *SG&A* intensity on the one hand and business effectiveness on the other are not one and the same phenomenon. More precisely, we have provided evidence that the decrease in business effectiveness subsumes the increase in *SG&A* intensity. Higher *SG&A* intensity is associated with lower business effectiveness, but the latter can occur without high levels of intangible investments (Figure 4).

The above argument explains how our findings cohere with those in Srivastava (2014).

The analysis in Srivastava (2014) considers one macroeconomic trend (increase in the intangible expenditures of cohorts) but not the other. Controlling only for the level of *SG&A* intensity explains some of the progressive decline in EQ measures by virtue of the omitted variable bias phenomenon: the coefficient of a variable (*SG&A* intensity) correlated with the true determinant (business effectiveness) is statistically significant when the determinant is not one of the explanatory variables. However, once the likely explaining factors, i.e., the business effectiveness variables, are included in the explanatory set, the bias is eliminated, and the coefficient of *SG&A* intensity becomes statistically insignificant (as we will see in the analysis in the next section).

6 . Statistical evidence supporting our narrative

Formal support for this narrative is presented in two steps. The first is to put forward evidence that *SG&A* intensity is subsumed by business effectiveness in relation to EQ measures. In a static analysis (performed on the pooled data from 1963 to 2016; see Section 6 .1) that regresses the EQ measures on the *SG&A* intensity, the coefficient of the latter is strongly statistically significant (positive for earnings volatility and EFP and negative for matching). However, when the business effectiveness proxies are added to the explanatory variables, only the coefficients of the latter are significant, while the coefficient of *SG&A* intensity becomes statistically equal to 0.

The first set of analyses found a statistically consistent association of EQ measures with measures of profitability, operational efficiency, and economic risk but not with the level of intangible expenditure (as measured by *SG&A* intensity, *R&D* expenses, or the intangible investment measure in (Enache and Srivastava, 2018); see also Section A.3 in the Appendix).

In the second step, the static regressions are complemented by dynamic analyses, performed cross section by cross section (results reported in Section 6 .2). These analyses directly investigate which of the two mechanisms of change, i.e., the evolution towards a knowledge-based economy vs. financial development, provides a more plausible explanation of the evolution of EQ measures. We expect changes in the cross section composition along the dimensions suggested by the most plausible narrative to explain (most of) the evolution of the EQ measures.

More concretely, we compare the magnitudes of the reduction in the differences between cohort mean EQ measures when controlling, cross section by cross section, for the level of firm $SG\&A$ intensityon the one hand and the levels of the business effectiveness variables on the other. Controlling with the set of variables whose evolution determines that of the EQ measures should remove most of the cross-sectional differences among cohort mean EQ measures. Controlling with the other set of variables (which are, as we have seen, only correlated with the first but do not explain the dynamic of EQ measures) should result in a moderate reduction (if any) in the differences among cohort mean EQ values.

6 .1. Which firm characteristic explains EQ, SG&A intensity or business effectiveness?

We ran two panel regressions (with time- and firm-fixed effects) for each EQ measure, which differ based on the set of independent variables. The first set contains only the $SG\&A$ intensity :

$$EQ_i = \gamma_0 + \gamma^{(u)}\ (SG\&Ai)_i + \varepsilon_i. \tag{8}$$

The estimated coefficients $\gamma^{(u)}$ (uncontrolled) reflect the association without controlling for possible bias due to omitted characteristics. The second set adds the firm characteristics that proxy for profitability, operational efficiency, and economic risk (relative to the industry's third quartile):

$$EQ_i = \gamma_0 + \gamma^{(c)}(SG\&Ai)_i + \gamma_1(CFO/SALE)_i + \gamma_2(SALE/AT)_i + \gamma_3\sigma(CFO)_i + \varepsilon_i. \quad (9)$$

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

	NI volatility		**Matching**		**EFP**	
SG&Ai	0.83**	0.27	-0.14*	-0.07	0.35^{+}	0.07
	(2.92)	(1.21)	(-2.58)	(-1.33)	(1.96)	(0.42)
Profitability		-0.69***				-0.95***
		(-4.40)				(-6.19)
Efficiency				0.02***		
				(4.03)		
Risk		4.58***		-0.33*		1.79***
		(9.23)		(-2.26)		(5.12)

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '+'

Table 3: **Static regressions - *SG&A* intensity.** This table reports the coefficients in the regressions (8) and (9) together with the t-statistics (in parenthesis) for testing the null hypothesis of the zero coefficient. Two columns correspond to each dependent variable (earnings volatility, matching, and *EFP*), first for the specification (8) and second for the specification (9). The t statistics are heteroscedasticity- and cluster-consistent (Petersen, 2008). The missing firm characteristic coefficients are statistically insignificant. The results show that the association of intangible intensity to the *EQ* measures under discussion is spurious: it disappears when we control for the profitability, operational efficiency, and economic risk of the firm.

Including both time- and firm-fixed effects addresses the issue of omitted variable bias due to the fact that the estimated associations may vary among firms and over time. In particular, the process of incorporating economic news into earnings and prices is firm-specific due to corporate governance mechanisms, internal controls, or relationships with the auditor, all of which are quite stable over time but not easily accessible to the researcher. Hence, this fact needs to be considered when designing the research strategy (Amir et al., 2016). Further, the ratios we use as independent variables have a strong industry-specific component. However, the firm effect subsumes the industry effect, ensuring that the estimation appropriately reflects the differences in ratio magnitude caused by industry/firm-specific characteristics. The t statistics we report are heteroscedasticity- and cluster-consistent (Petersen, 2008).

The results of the six regressions are presented in table 3. The t statistics are based on heteroscedasticity-consistent standard errors clustered by firm and time.[19] In uncontrolled regressions (8), *SG&A* intensity is, as expected, positively associated with earnings volatility and earnings pertinence to prices and negatively associated with matching. In controlled regressions (9), the coefficients of *SG&A* intensity become statistically equal to 0. In contrast to this, the coefficients of firm characteristics are strongly significant. Profitability is negatively associated with the volatility of earnings and positively associated with matching. Cash flow volatility is positively associated with volatility of earnings and earnings pertinence to prices and negatively associated with matching. As expected, asset utilization is positively correlated with matching.

To summarize, the results in table 3 show that in a static setup the association of intangible intensity and the EQ measures under discussion is spurious. That is, it disappears when we control for the effectiveness of the business (as measured by profitability, operational efficiency, and economic risk).We will see in the next section that controlling for these characteristics in cross-sections greatly reduces the "listing effect" dynamic of the three EQ measures seen in Figure 3, while controlling for the level of *SG&A* intensity does not.

[19]This approach is unbiased as long as there are a sufficient number of clusters. In this case, there are both enough firms and enough time periods (Petersen, 2008).

6 .2. What explains the cross-sectional differences among cohorts' mean EQ values?

The statistical setup of the analyses in this section is that described in Section 3 .3. For each of the EQ measures, the results are presented in three graphs. Each graph reports the outcomes of a large number of hypothesis tests, as detailed in Section 3 .4.

To establish a benchmark, we estimate the simple regression (5) for each of the three EQ measures and on each cross section t between 1970 and 2016:

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

where $D^{(Co_j)}$ stands for the dummy variable corresponding to membership in cohort j. This step quantifies and tests the differences between averages of the EQ measure conditional on the cohort.

The first graph of each sequence of three graphs we construct for each EQ measure reports the coefficients

$$\beta_j(t) = \mathbb{E}[EQ_t) \,|\, Co_j] - \mathbb{E}[EQ_t) \,|\, Co_0], \tag{10}$$

and their one-sided 95% confidence levels as a function of t, the fiscal year. The coefficients (10) represent the difference between the mean EQ of the latter cohort j and the mean EQ measure of the cohort of pre-1970 firms. 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 increasing order for earnings volatility and EFP and in decreasing order for matching).

For each of the three EQ measures, we performed two further time series analyses based on the following multiple regression (6):

$$EQ_{i,t} = \mu(t) + \beta_1(t)D_{i,t}^{(Co_1)} + \ldots + \beta_m(t)D_{i,u}^{(Co_m)} + \gamma(t)Ch_{i,t} + \varepsilon_{i,t},$$

where *Ch* stands first for *SG&A* intensity and second for the business effectiveness proxies defined in Section 4 .1 (profitability, efficiency, and risk, the evolution of which are presented in Figure 4). The estimation of the cross-sectional multiple regressions reveals evidence on the degree of association between changes in firms' *SG&A* intensity and business effectiveness proxies and the decline in *EQ* measures. The results are reported in the central column (controlling for *SG&Ai*) and in the right-hand column (controlling for business effectiveness) of Figure 5. These graphs display the coefficients

$$\beta_j(t) = \mathbb{E}[EQ_t \,|\, Co_j, Ch \in \mathscr{S}] - \mathbb{E}[EQ_t \,|\, Co_0, Ch \in \mathscr{S}] \tag{11}$$

and their one-sided 95% confidence levels as a function of t, the fiscal year, where $\mathscr{S} = \{SG\&Ai\}$ (central column) and $\mathscr{S} = \{CFO/SALE,\ SALE/AT,\ \sigma(CFO)\}$ (right-hand column), respectively. The shaded areas dropping from (or surrounding) the curves $\beta_j(t)$, $j = 1,2,3,4$ represent the 95% one-sided confidence bands for the difference (10) in the left-hand side graphs and (11) in the other graphs, respectively. The x-axis outside shaded area corresponding to the curve $\beta_j(\cdot)$ is statistically significant evidence of lower *EQ* in firms belonging to the cohort j with respect to the 1960–1969 reference Co_0. To put it simply, the closer the four curves are to 0, the more changes in the controlled fundamental firm characteristics explain the differences in the cohort *EQ* measures.[20]

Figure 5 presents the results. These reveal that controlling with *SG&A* intensity ex-

[20]For an argument explaining the motivation of the graphical choice of presenting the results of the formal statistical analysis as well as the articulation with the tabular presentation which is the custom in the accounting literature, we refer the reader to Section 3 .5; note that the information displayed graphically is the same with that contained in a regular table tabulating the point estimates and their *SE*.

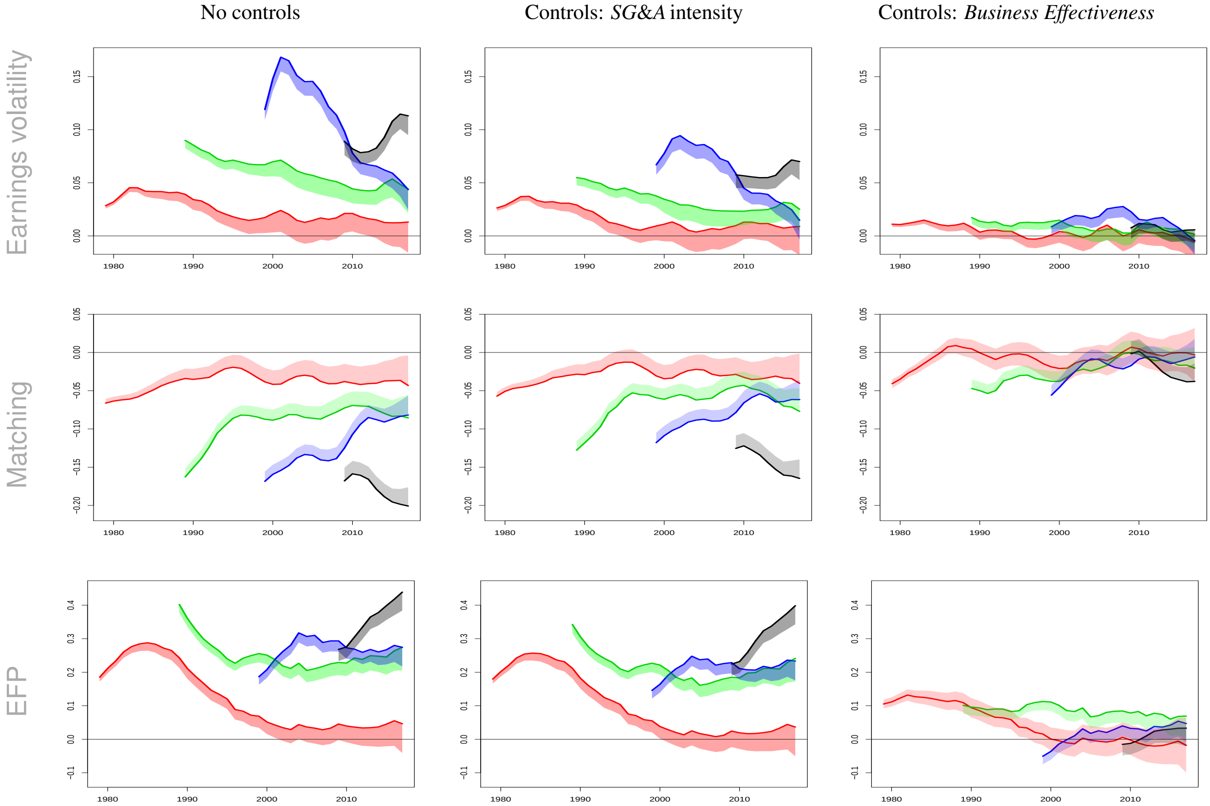

Figure 5: **The evolution of cohort mean EQ measures – controls and hypothesis tests**. The curves track the coefficients $\beta_j(t)$ (j from 1 to 4; color-coded red, green, blue, and black, in increasing order) in the simple cross-sectional regression (5)(top-left) and in the multiple cross-sectional regression (6), where the controlling characteristic(s) appear in the title of the graphs as a function of t, the year. The shaded areas dropping from (or surrounding) the curves $\beta_j(t)$, $j = 1,2,3,4$, represent the 95% one-sided confidence bands for the difference $\mathbb{E}[EFP(NI)_t\,|Co_j] - \mathbb{E}[EFP(NI)_t\,|Co_0]$ for the first graph and$\mathbb{E}[EFP(NI)_t\,|Co_j, Ch] - \mathbb{E}[EFP(NI)_t\,|Co_0, Ch]$ for the other graphs. The x-axis outside the shaded area k is statistically significant evidence of lower EQ for firms belonging to the cohort j with respect to the 1960–1969 reference Co_0. Controlling with *SG&A* intensity explains a relatively small part of the differences between the later cohorts and the reference cohort. Controlling for the level of the three business effectiveness variables explains most of this difference.

plains little (if any) of the differences between newer cohorts and the reference, while controlling for the components of business effectiveness explains most of the differences between the EQ measures of the later cohorts and that of the 1960–1969 reference.The graphs in the figure are substantial evidence for the narrative that associates the decrease in EQ measures to the arrival of progressively weaker firms to the market.

7 . What has (mostly) changed: EQ measures or cross section structure?

The previous section examined what happens to the differences between the different cohorts' mean EQ measures when we control for the level of intangible intensity or the levels of the business effectiveness variables. In this section, we evaluate the impact of the same controls on the overall downward trend of the three EQ measures. For each of the three EQ measures, we cross-sectionally estimate the following regression:

$$EQ_{i,t} = \mu(t) + \gamma(t)Ch_{i,t} + \varepsilon_{i,t},$$

where Ch stands first for *SG&A* intensity and second for the business effectiveness proxies defined in Section 4 .1 (the measures of profitability, efficiency, and risk relative to the industry's third quartile, the evolution of which are presented in Figure 4). We display the functions $t \to \mu(t)$ together with heteroscedastically-consistent 95% confidence intervals. The results are presented in Figure 6, in which a robust regression line has been added to help make clear the trend in the estimated time series of intercepts. The left-hand column presents the time series of cross-sectional means of the EQ measures together with the heteroscedastically-consistent 95% confidence intervals. This shows a very pronounced evolution in the mean EQ measures towards lower levels of quality. The middle column displays the evolution of the mean EQ measures when controlling for the firms' level of *SG&A* intensity. The evolution towards lower levels of quality is still visible, but it is significantly reduced.

Finally, the right-hand column displays the dynamics of the mean EQ measures when controlling for the firms' business effectiveness variable levels. This column reveals that if we control for the changes in the composition of the cross section related to the business effectiveness variables, the EQ measures do not display a significant trend.

Figure 6: **The evolution of the cross-sectional mean of** EQ **measures.** The plots display the evolution of the cross-sectional mean of the three EQ measures uncontrolled (left column), controlled with the firm level of *SG&A* intensity (center column), and controlled with the business effectiveness variables (i.e., profitability, efficiency, and economic risk; right-hand column). The graphs display the mean (solid black line), the heteroscedastically-consistent 95% confidence interval for the mean (dotted red lines), and a robust regression line fitted over the estimated mean values (dashed blue line) to mark the trend in the evolution of cross-sectional EQ mean. The EQ measures are specified in the labels on the left-hand side of the figure in the first column. The left-hand column shows a pronounced decline in cross-sectional mean EQ measures. Controlling with firm *SG&A* intensity reduces the trend in the evolution of the mean EQ measures, while controlling for the business effectiveness variables removes it.

As new firms arrive into the cross section and older firms leave it, its structure evolves and with it the values of the EQ measures. The fact that the robust regression line is flat and always inside the confidence interval provides evidence that all of the evolution towards lower levels of EQ quality in the left-hand columns of the graphs is due to changes in the composition of the cross section related to the business effectiveness variables.

To conclude, the EQ measures have not changed significantly over the past five decades.

The reason they seem to have a downward trend lies in the progressive change in the structure of the cross section along the business effectiveness dimensions. Once we control for these cross-sectional structural changes, the downward trend disappears.

8 . Robustness

Our results are robust to a number of possible specifications. First, we estimated the non-linear regression, yielding the EFP measure using non-linear methods other than RF. We used the conservatism index in Penman and Zhang (2002) as an alternative measures of the level of conservatism to the P/B ratio. Further, we used total assets as an alternative to market value as a proxy for risk.

Second, we measured the matching of revenues and expenses by the $b_{3,i}$ coefficient in the firm-specific matching regression:

$$Revenues_{i,u} = b_{1,i}(t) + b_{2,i}(t)\ Total\ Expenses_{i,u-1} + b_{3,i}(t)\ Total\ Expenses_{i,u} + b_{4,i}(t)\ Total\ Expenses_{i,u+1} + \varepsilon_{i,u}.$$

Third, we implemented and evaluated other measures quantifying the intangible investments in the extant literature (see, e.g., Banker et al., 2011; Brown and Kimbrough, 2011; Eisfeldt and Papanikolaou, 2013; Enache and Srivastava, 2018). While some of these alternative measures do not seem fit for the purpose of the present analysis, the others give qualitatively equal results to the ones obtained using the ratio between $XSGA$ and total expenses (see the detailed analysis in Section A.3 in the Appendix). Finally, we used the alternative balance sheet and income statement measures of profitability to assess firms' business effectiveness (see section A.4 in the Appendix).

9 . Conclusions

We have argued that the evolution in *EQ* measures documented by Srivastava (2014) reflects changes in the structure of the cross section of firms arising as a result of the development of the U.S. financial sector (Rajan and Zingales, 2003). As funding becomes easier to obtain, progressively weaker firms gain access to equity financing (Fama and French, 2004). Consequently, the cross-sectional *EQ* measures steadily deteriorate, reflecting the decreasing effectiveness of the cross-sectional firm population. For firms in high intangible intensity industries, which represent between 20% and 45% of the newer cohorts, the decline in the business effectiveness is associated with, and possibly accentuated by, an increase in *SG&A* intensity. For the rest of the firms, i.e., the strict majority of all cohorts, the average business effectiveness deteriorates despite the fact that the level of intangible intensity does not change. While the increase in intangible intensity is associated with lower business effectiveness, the former does not seem to be the cause of the latter.

The downward trends in both EQ measures and business effectiveness continue unabated even after the expansion of the U.S. public market comes to an end around the year 2000. At this point, U.S. financial development enters into a new phase in which, while the ease of access to equity funding does not decline, a significant shift from public to private financing becomes noticeable, especially for firms with mostly intangible assets.

This narrative developed in this paper contrasts with the one developed in Srivastava (2014), which attributes the evolution of *EQ* measures to "the widening gap between the intangible intensities of the new- and seasoned-firm segments," a consequence of the evolution of the U.S. economy from an industrial to a knowledge-based economy. We argue that this explanation is at most only part of the story and that the setup in the cited paper does not properly consider other mechanisms of change. To address this issue, we refine the analysis in Srivastava (2014) by considering the impact on EQ measures made by the encompassing macroeconomic evolution, unfolding contemporaneously, towards lower cross-sectional average business effectiveness.

In the expanded setup, which allows for a horse race between the two explanations, we find that, while significantly negative when considered alone, the impact of intangible intensity on EQ measures disappears when we control for fundamental characteristics measuring the business effectiveness of firms. In a setup that accommodates both explanations and allows them to compete, it is only the latter that maintains an association with EQ measures.[21]

Which of the two narratives is a better explanation for the decline of the EQ measures is important for the ongoing debate on measuring the quality of earnings. If the increase in intangible intensity is at the bottom of the decline in EQ, the trend might be interpreted by some as evidence for the lack of fit of the EQ measures under discussion to appropriately record the risks and returns of intangible investments. The firm population would be equally strong economically, but the EQ measures would have plummeted. If, on the contrary, the explanation for declining EQ lies in the facilitated access to equity financing for less profitable, less efficient, riskier firms, the downward trend is evidence of well-functioning EQ measures that recognize and quantify the decreasing effectiveness in the firm population.

Finally, we found that EQ measures have not significantly changed over the last five decades. The reason they seem driven by a downward trend lies in the progressive change in the structure of the cross section of firms along the business effectiveness dimensions

[21] In statistical terms, the analysis in Srivastava (2014) is affected by omitted variable bias.

of profitability, operational efficiency, and economic risk. When holding the cross section structure constant along these dimensions, the pattern of average yearly EQ measures over the past fifty years remains flat.

The contribution of our paper is thus to bring to light the inter-linkages between the following results in accounting and financial economics literature: (1) Srivastava (2014) shows that the progressive declines in EQ measures are largely the result of the assimilation of successive cohorts of newly listed firms into the firm population; (2) Rajan and Zingales (2003) identify a change in the trend in financial market development around the 1970s; (3) Fama and French (2004) show that newly listed companies have weaker fundamentals and propose a mechanism that ties this finding to the development of the U.S. financial sector; and, finally, (4) Kahle and Stulz (2017), Doidge et al. (2017), and Doidge et al. (2018) argue that financial market development recently entered a new phase characterized by a decrease in the net benefit for a firm to be listed (in particular for firms with unproven intangible assets).

A. Appendix

A.1. Value relevance research design

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

Holthausen and Watts (2001) gives 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 frequently employed specification of the research design triad in such studies is composed of Ohlson's linear solution to the RI equation (as a valuation model), the price-levels regression (or returns–earnings regression[22]) estimated on cross-sectional data (as empirical stipulations of the model)

$$P_{i,t} = \beta_0 + \beta_1 NI_{i,t} + \beta_2 B_{i,t} + \varepsilon_{i,t},$$

and the regression's R^2 (as a measure of association).

Extant literature has highlighted issues concerning each one of the three elements of the mentioned research design. First, the Ohlson version of the RI model has shortcomings tied to the linear assumptions regarding the dynamic of the residual earnings (Holthausen and Watts, 2001). Second, the estimation of price-levels and returns–earnings regressions is potentially impaired by bias, due on the one hand to error terms correlated with the independent variables (Lo, 2005; Barth and Clinch, 2009) and on the other hand to coefficients that are functions of firm-specific risk characteristics and industry-specific dynamics of residual earnings (Kothari and Shanken, 2003) and are hence not cross-sectionally constant.[23] 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 combination makes it difficult to trace whether a change in explanatory power is due to differences in the economic relation or to differences between samples.

The alternative research design begins from the observation that a non-linear regression relation will always exist between prices and earnings (while a linear regression most likely will not). Hence, the price $P_{i,t}$ can be decomposed into the sum of the best non-linear prediction of value based on the observed earnings ($\mathbb{E}[P_{i,t}\,|\,NI_{i,t}]$) along with an adjustment term that reflects all other information available to investors:

$$P_{i,t} = \mathbb{E}[P_{i,t}\,|\,NI_{i,t}] + \varepsilon_{i,t} := \mathbf{m}_i(NI_{i,t}) + \varepsilon_{i,t}. \tag{12}$$

Here, $\mathbb{E}[P_{i,t}\,|\,NI_{i,t}]$ stands for the conditional expectation[24] of P given NI. From a statistical point

[22]While, for the sake of simplicity we make our argument around the price-level regression, it also applies to the returns–earnings regressions

[23]One can prove that these two causes of inconsistency are 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 *raison d'être* of the two specifications, is not itself a regression. Consequently, its two empirical specifications are by definition ill-suited to consistent estimation.

[24]It is a well-known fact that $\mathbb{E}[P\,|\,NI]$ is a (generally) non-linear function of NI. It is also the best

of view, investors' adjustments are a regression error term that is orthogonal to the predictor ($\mathbb{E}[\varepsilon_{i,t}\,|\,NI_{i,t}] = 0$). This condition guarantees the consistent estimation of $\mathbf{m}$ and is violated if a linear regression is estimated when the economic relation is in fact non-linear.

Non-linear regression. Estimating a linear relation between earnings and price when the true regression is non-linear yields coefficients that do not reflect the economic relation in (12) and that, consequently, cannot be used to test hypotheses[25] (see Starica and Marton, 2020).

In contrast to this, the non-linear function $\mathbf{m}$ presented in (12) can always be consistently estimated on cross-sections of firms by employing proven inference techniques from the field of non-parametric regression.

Valuation models and accounting considerations help outline the empirical specifications. Assuming that prices follow the residual income (RI) valuation relation (Preinreich, 1936, 1938; Edwards and Bell, 1961; Peasnell, 1982)

$$P_{i,t} = B_{i,t} + \sum_{u=1}^{\infty} \frac{\mathbb{E}_t[NI_{i,t+u} - r_{i,t} \times B_{i,t+u-1}]}{(1+r_{i,t})^u} = B_{i,t} + \sum_{u=1}^{\infty} \frac{\mathbb{E}_t[RI_{i,t+u}]}{(1+r_{i,t})^u}, \tag{13}$$

(r_t denotes the price of equity risk at time t, $\mathbb{E}_t$ stands for the market's expectation conditional on all information available at time t, while RI stands for the abnormal earnings $NI - r \times B_{-1}$), Starica and Marton (2020) show that the non-linear regression function $\mathbf{m}$ in the decomposition (12) can be expressed as:

$$\mathbf{m}_{i,t}(NI_{i,t}) = B_{i,t} + \sum_{u=1}^{\infty} \frac{\mathbb{E}[RI_{i,t+u}\,|\,NI_{i,t}]}{(1+r_{i,t})^u}. \tag{14}$$

By comparing the expression in (14) to the RI representation (13), it can be seen that the non-linear regression function $\mathbf{m}$ is a valuation according to which the the expectations of future abnormal earnings are informed only by the level of earnings $NI_{i,t}$.

The main factors driving the future evolution of abnormal earnings are a firm's risk, its growth profile, and possibly accounting determinants (for example, unconditional conservatism[26]). Consequently, we expect that, while the regression function (14) is firm-specific, firms with similar levels of risk, growth, and accounting conservatism will have roughly the same regression function:

$$\mathbf{m}_{i,t}(NI_{i,t}) = \mathbf{m}_t(NI_{i,t};\, r_{i,t},\, g_{i,t},\, ACC_{i,t}),$$

where $r_{i,t}$ stands for a firm's risk, g_i denotes its growth, and C_i a measure of its accounting determinants. Hence, for the firms in a cross section t, we estimate[27] the following empirical specification of the economic relation (13):

$$P_{i,t} :=\ \mathbf{m}_t(NI_{i,t};\, r_{i,t},\, g_{i,t},\, ACC_{i,t}) + \varepsilon_{i,t},$$

where the error term $\varepsilon_{i,t}$ satisfies the orthogonality condition

$$\mathbb{E}_t[\varepsilon_i\,|\,NI_i] = 0.$$

predictor (in the L^2-norm) of P given NI.

[25]This is, fundamentally, the explanation of the well-known bias issue that affects price-levels or returns–earnings regressions (Lo, 2005), Barth and Clinch (2009)). Estimating a non-linear regression resolves the issue.

[26]How current abnormal earnings forecast future earnings might depend on how the earnings are constructed.

[27]We apply a non-parametric approach to non-linear regression estimation that is widely used in the machine learning and artificial intelligence applications (see Section 4 .1 for details).

We discuss the proxies for risk, growth, and accounting determinants in Section 4 .1.

A.2. Sample

Figure A.1 displays the evolution of the number of firms in the sample (left) and in the cohorts (right). The number of firms in a cohort increases between the year of the cohort's creation at the beginning of the decade and the end of the decade and then decreases steadily as firms are delisted.

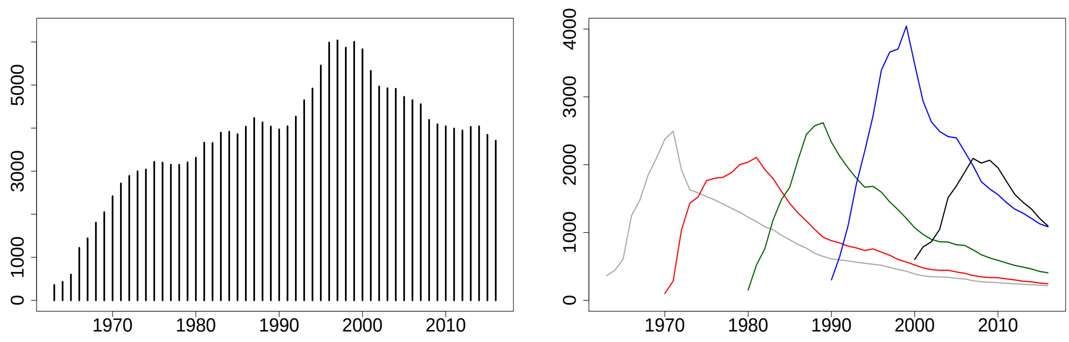

Figure A.1: **Evolution of sample size.** The left-hand graph displays the evolution of the number of firms in the cross-section. The right-hand graph shows the evolution of the cohort size.

We note an increase in the cohort size for the 1980, 1990, and 2000 cohorts, followed by a reduction in the size of the 2010 cohort, most likely caused by the new phase in the U.S. financial development characterized by a significant shift from public to private financing, especially for firms with mostly intangible assets (Kahle and Stulz, 2017; Doidge et al., 2017, 2018).

A.3. Other measures of intangible investment

This section investigates the performance of other intangible investment measures proposed in the literature. We put forward evidence that some measures do not display the pattern of increased intangible investment in newer cohorts, a prerequisite for being used in the type of analysis we perform. Other proxies give qualitatively similar results to the *SG&A* intensity used in our analysis and support our findings.

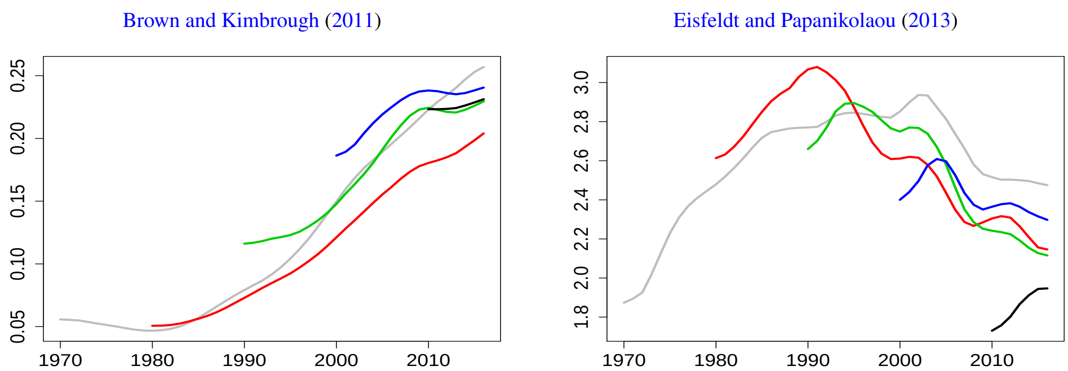

Figure A.2: **Time evolution of alternative measures of intangible investment – 1.** The plots display cohorts' median intangible intensity from Brown and Kimbrough (2011) (left) and the stock of the organization capital measure from Eisfeldt and Papanikolaou (2013). The median is estimated over a three-year moving window. Neither of the two measures is likely to explain the cohort differences in the *EQ* measures documented in figure 3.

The graphs in Figure A.2 display the median values of the other two measures for the cohorts' intangible intensity introduced in Brown and Kimbrough (2011) and Eisfeldt and Papanikolaou (2013), respectively. Brown and Kimbrough (2011) defines the measure of intangible intensity as the average of $(INTAN + GDWL + XRD)/(AT + XRD)$ over a given number of past quarters. For the graph in Figure A.2, we calculated the average over the past eight years. Eisfeldt and Papanikolaou (2013) construct their stock of organization capital measure cumulating the value of SG&A expenses by the perpetual inventory method and expressing them as a percentage of firm book assets. The graph in Figure A.2 is constructed using a depreciation rate of 85% (the same as in Eisfeldt and Papanikolaou (2013)) and the SG&A expenses from the past eight years (if the SG&A is missing, the year is not counted). This approach aims to measure the remaining useful value of past investments that could potentially be presented in a balance sheet.

The plots in Figure A.2 indicate that neither of the two measures of intangible intensity is likely to explain the differences in the EQ measures among cohorts documented in Figure 3. The median cohort values of the intangible intensity in Brown and Kimbrough (2011) are almost indistinguishable. Moreover, neither of the two graphs reveal an increase in the intangible intensity of younger cohorts. At the end of the sample, the 1970 cohort has a median value that is smaller only than that of the 2000 cohort.

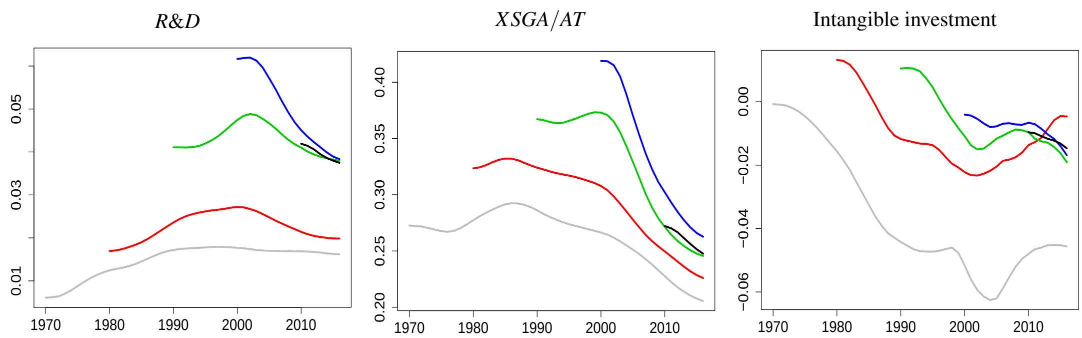

Figure A.3: **Time evolution of alternative measures of intangible investment – 2.** The plots display cohorts' median firm characteristic values estimated over a three-year moving window. The variables are specified in the graph's title.

We also implemented $R\&D$ expenses (as a percentage of total assets), $SG\&A$ expenditure deflated by total assets from Banker et al. (2011), as well as Enache and Srivastava (2018)'s refinement of the $SG\&A$ intensity measure, which first deducts $R\&D$ and advertising outlays from SG&A and then divides the remaining quantity (which they refer to as Main SG&A) into a maintenance and an investment component. The intuition is that the former contains outlays that vary with current revenues, while the latter is the part of the SG&A that does not commingle with operating expenses.

In contrast to the two measures mentioned above, the graphs in Figure A.3 indicate that $R\&D$ expenses, $SG\&A$ expenditure deflated by total assets, and the intangible investment measure of Enache and Srivastava (2018) display a clear pattern in relation to cohort structure. The$R\&D$ proxy ($SG\&A$ expenditure deflated by total assets) is constructed as the median of at least four values of the eight most recent annual observations ($t-7$ through t) of the ratio of XRD ($XSGA$) to AT. For a definition of the other proxy, see Section 4 .1 and Enache and Srivastava (2018).

Next, we present the results of the analysis in Section 6 .1 using $R\&D$ (Table A.1), $XSGA/AT$ (Table A.2), and the proxy defined in Enache and Srivastava (2018) (Table A.3) as alternative intangible investment measures to $SG\&A$ intensity.

Similar to the results in Section 6 .1, in uncontrolled regressions (8) the intangible investment proxies are significantly positively associated with earnings volatility and earnings pertinence to

	NI volatility		Matching		EFP	
R&D	2.59***	0.37	-0.29*	-0.16	1.76***	0.52
	(4.57)	(1.03)	(-2.40)	(-1.51)	(3.34)	(1.00)
Profitability		-0.70***				-0.47***
		(-4.48)				(-4.35)
Efficiency				0.03***		
				(3.66)		
Risk		4.58***		-0.32***		1.23***
		(9.07)		(-2.85)		(3.53)

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '+'

Table A.1: **Static regressions – *R&D*.** The table reports the coefficients in the regressions (8) and (9) together with the t-statistics (in parenthesis) for testing the null hypothesis of the zero coefficient. Two columns correspond to each dependent variable (earnings volatility, matching, and EFP), one for each of the two specifications: (8) and (9). The t statistics are heteroscedasticity- and cluster-consistent. The missing firm characteristic coefficients are statistically insignificant. The results show that the association of *R&D* to the EQ measures under discussion is spurious: it disappears when we control for the profitability, operational efficiency, and riskiness of the firm.

	NI volatility		Matching		EFP	
$XSGA/AT$	0.25*	0.15	-0.01	-0.01	0.12***	0.06
	(2.34)	(1.92)	(-1.39)	(-1.48)	(3.19)	(1.50)
Profitability		-2.42***				-2.33***
		(-5.86)				(-9.97)
Efficiency				0.02***		
				(4.70)		
Risk		5.39***		-0.29*		1.48***
		(8.37)		(-2.62)		(5.50)

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '+'

Table A.2: **Static regressions - $XSGA/AT$ (Banker et al., 2011).** The table reports the coefficients in the regressions (8) and (9) together with the t statistics (in parenthesis) for testing the null hypothesis of the zero coefficient. Two columns correspond to each dependent variable (earnings volatility, matching, and EFP), one for each of the two specifications: (8) and (9). The t statistics are heteroscedasticity- and cluster-consistent. The missing firm characteristic coefficients are statistically insignificant. The results show that the association of the intangible investment measure of Enache and Srivastava (2018) to the EQ measures under discussion is spurious: it disappears when we control for the profitability, operational efficiency, and riskiness of the firm.

prices and negatively associated with matching. However, in controlled regressions (9) the coefficients of the intangible investment proxies become statistically equal to 0. In contrast to this, the firm characteristics' coefficients are strongly significant. Profitability is negatively associated with the volatility of earnings and positively associated with matching. Cash flow volatility is positively associated with the volatility of earnings and earnings pertinence to prices and negatively associated with matching. As expected, asset utilization is positively correlated with matching. Once again, the results show that in a static setup, the association of intangible investment to the EQ measures under discussion is spurious, that is, it disappears when we control for the effectiveness of the business.

Due to space limitations, we do not report the results of the dynamic analysis in Section 6 .2 performed using the intangible investment measures *R&D*, $XSGA/AT$, and the proxy defined in Enache and Srivastava (2018) as a replacement for *SG&A* intensity. They are qualitatively equal to the results displayed in Figure 5 and are available upon request.

	NI volatility		Matching		EFP	
Intangible Investment	0.33*** (3.29)	0.09 (1.16)	-0.03** (-2.69)	-0.02 (-1.46)	0.36*** (3.13)	0.26 (1.81)
fig:htProfitability		-0.79*** (-4.14)				-0.68*** (-4.55)
Efficiency				0.01*** (4.56)		
Risk		4.88*** (8.49)		-0.19*** (-3.68)		1.39*** (3.89)

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '+'

Table A.3: **Static regressions - Intangible investments (Enache and Srivastava, 2018).** The table reports the coefficients in the regressions (8) and (9) together with the t statistics (in parenthesis) for testing the null hypothesis of the zero coefficient. Two columns correspond to each dependent variable (earnings volatility, matching, and EFP), one for each of the two specifications (8) and (9). The t statistics are heteroscedasticity- and cluster-consistent. The missing firm characteristic coefficients are statistically insignificant. The results show that the association of intangible investment measure of Enache and Srivastava (2018) to the EQ measures under discussion is spurious: it disappears when we control for the profitability, operational efficiency, and riskiness of the firm.

A.4. Other measures of business effectiveness

In this section, we present evidence that the decline in profitability documented through the evolution of the cohort median (industry) rank of the $CFO/SALES$ ratio shown in Figure 4 is visible in other balance sheets as well as in income statement profitability proxies. The graphs on the left-hand side of Figure A.4 display the median ranks of the cohorts' profit margins ($IB/SALES$), ROE, ROA, and $CFO/SALES$.

The graphs in Figure A.4 show a pattern of decreased profitability for newer cohorts independent of the measure used. Our robustness analyses showed that the results presented in Sections 6 .1 and 6 .2 hold when replacing the $CFO/SALES$ with any of the profitability measures above.

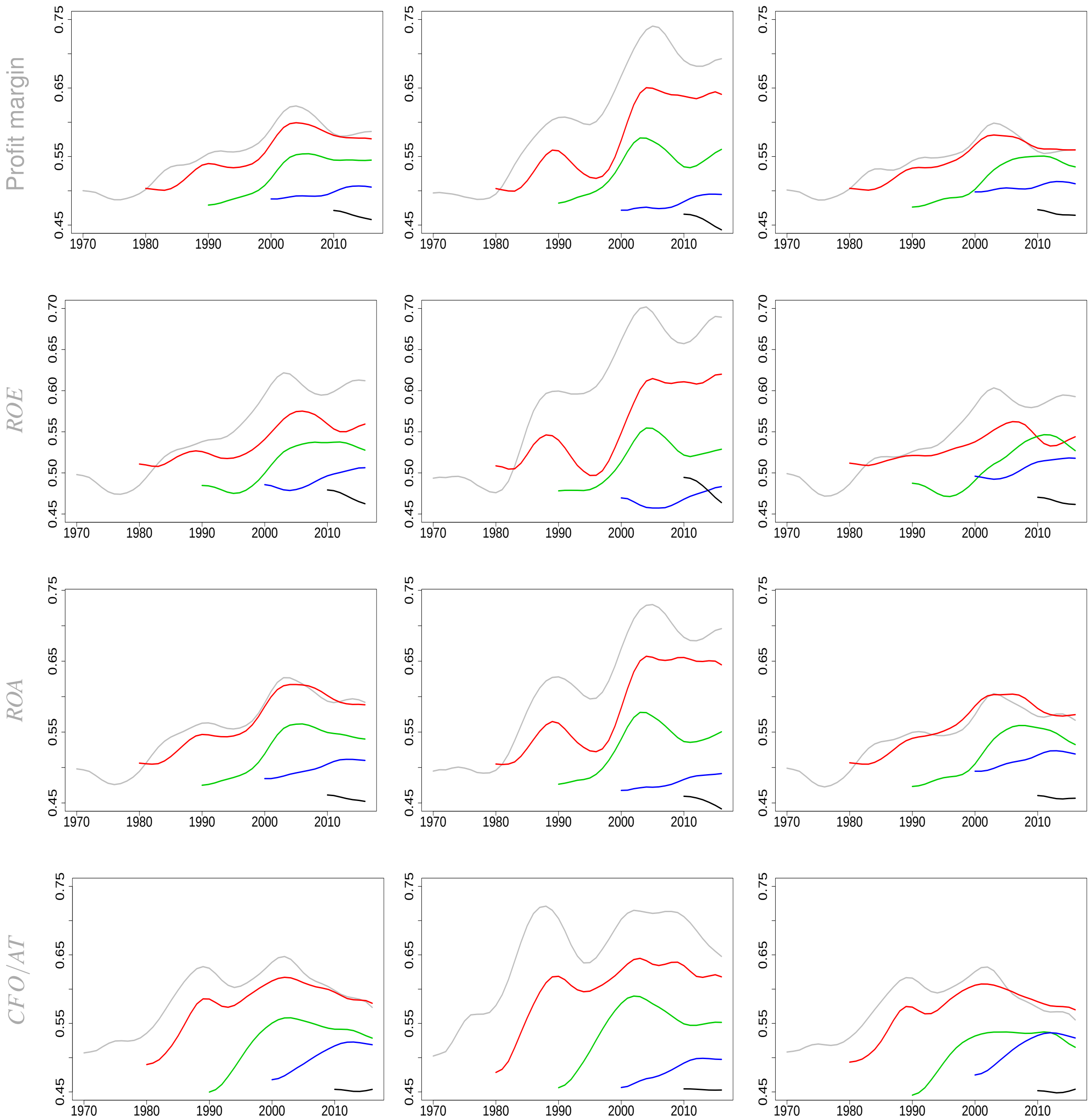

Figure A.4: **Time evolution of other firm characteristics measuring profitability.** For a given cross section and for each industry we rank the firms in the industry based on the values of the business effectiveness variables under study and use a firm's rank within its industry (on a scale from 1 to 100) as a relative measure of effectiveness. The plots display cohorts' mean ranks regarding firm business effectiveness characteristics (indicated in the title on the left of figure) within the firms' industry (Fama French 48 industry classification). The means are smoothed over a three-year moving window. The graphs document an overall decline in profitability proxies, manifest in both low and high intangible intensity sectors of the economy.

References

Amir, E., Carabias, J. M., Jona, J., and Livne, G. (2016). Fixed-effects in empirical accounting research. Technical report, Available at SSRN: https://ssrn.com/abstract=2634089.

Banker, R. D., Huang, R., and Natarajan, R. (2011). Equity incentives and long-term value created by SG&A expenditure. *Contemporary Accounting Research*, 28(3):794–830.

Barth, M. and Clinch, G. (2009). Scale effects in capital markets-based accounting research. *Journal of Business Finance and Accounting*, 36(3-4):253–288.

Barth, M. E., Landsman, W. R., and Lang, M. H. (2008). International accounting standards and accounting quality. *Journal of Accounting Research*, 46(3):467–498.

Brown, G. and Kapadia, N. (2007). Firm-specific risk and equity market development. *Journal of Financial Economics*, 84(2):358 – 388.

Brown, N. C. and Kimbrough, M. D. (2011). Intangible investment and the importance of firm-specific factors in the determination of earnings. *Review of Accounting Studies*, 16(3):539–573.

Collins, D., Maydew, E., and Weiss, I. (1997). Changes in the value-relevance of earnings and book values over the past forty years. *Journal of Accounting and Economics*, 24(1):39–67.

Dichev, I. D. and Tang, V. W. (2008). Matching and the changing properties of accounting earnings over the last 40 years. *The Accounting Review*, 83(6):1425–1460.

Dichev, I. D. and Tang, V. W. (2009). Earnings volatility and earnings predictability. *Journal of Accounting and Economics*, 47(1):160–181.

Doidge, C., Kahle, K. M., Karolyi, G. A., and Stulz, R. M. (2018). Eclipse of the public corporation or eclipse of the public markets? *Journal of Applied Corporate Finance*, 30(1):8–16.

Doidge, C., Karolyi, G. A., and Stulz, R. M. (2017). The U.S. listing gap. *Journal of Financial Economics*, 123(3):464 – 487.

Donelson, D. C., Jennings, R., and McInnis, J. (2011). Changes over time in the revenue-expense relation: Accounting or economics? *The Accounting Review*, 86(3):945–974.

Easton, P. D. and Harris, T. S. (1991). Earnings as an explanatory variable for returns. *Journal of Accounting Research*, 29(1):19–36.

Edwards, E. and Bell, P. (1961). *The Theory and Measurement of Business Income*. University of California Press.

Eisfeldt, A. and Papanikolaou, D. (2013). Organization capital and the cross-section of expected returns. *The Journal of Finance*, 68(4):1365–1406.

Enache, L. and Srivastava, A. (2018). Should intangible investments be reported separately or commingled with operating expenses? New evidence. *Management Science*, 64(7):3446–3468.

Fama, E. F. and French, K. R. (2004). New lists: Fundamentals and survival rates. *Journal of Financial Economics*, 73(2):229 – 269.

Givoly, D. and Hayn, C. (2000). The changing time-series properties of earnings, cash flows and accruals: Has financial reporting become more conservative? *Journal of Accounting and Economics*, 29(3):287 – 320.

Gu, Z. (2007). Across-sample incomparability of R^2s and additional evidence on value relevance changes over time. *Journal of Business Finance and Accounting*, 34(7-8):1073–1098.

Holthausen, R. W. and Watts, R. L. (2001). The relevance of the value-relevance literature for financial accounting standard setting. *Journal of Accounting and Economics*, 31(1–3):3–75.

Hribar, P. and Collins, D. W. (2002). Errors in estimating accruals: Implications for empirical research. *Journal of Accounting Research*, 40(1):105–134.

Irvine, P. J. and Pontiff, J. (2009). Idiosyncratic return volatility, cash flows, and product market competition. *The Review of Financial Studies*, 22(3):1149–1177.

Kahle, K. M. and Stulz, R. M. (2017). Is the us public corporation in trouble? *Journal of Economic Perspectives*, 31(3).

Kothari, S. P., Laguerre, T. E., and Leone, A. J. (2002). Capitalization versus expensing: Evidence on the uncertainty of future earnings from capital expenditures versus R&D outlays. *Review of Accounting Studies*, 7(4):355–382.

Kothari, S. P. and Shanken, J. (2003). Time-series coefficient variation in value-relevance regressions: A discussion of Core, Guay, and Van Buskirk and new evidence. *Journal of Accounting and Economics*, 34:69–87.

Lang, M., Smith Raedy, J., and Wilson, W. (2006). Earnings management and cross listing: Are reconciled earnings comparable to US earnings? *Journal of Accounting and Economics*, 42(1):255 – 283.

Lev, B. and Zarowin, P. (1999). The boundaries of financial reporting and how to extend them. *Journal of Accounting Research*, 37(2):353–385.

Lo, K. (2005). The effects of scale differences on inferences in accounting research:

Coefficient estimates, tests of incremental association, and relative value relevance. *SSRN Working Paper Series*.

Peasnell, K. (1982). Some formal connections between economic values and yields and accounting numbers. *Journal of Business Finance and Accounting*, 9(3):361–381.

Penman, S. H. and Zhang, X.-J. (2002). Accounting conservatism, the quality of earnings, and stock returns. *The Accounting Review*, 77(2):237–264.

Petersen, M. A. (2008). Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches. *The Review of Financial Studies*, 22(1):435–480.

Preinreich, G. (1936). The fair value and yield of common stock. *The Accounting Review*.

Preinreich, G. (1938). Annual survey of economic theory: The theory of depreciation. *Econometrica*.

Rajan, R. and Zingales, L. (2003). The great reversals: the politics of financial development in the twentieth century. *Journal of Financial Economics*, 69(1):5 – 50.

Sloan, R. G. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review*, 71(3):289–315.

Srivastava, A. (2014). Why have measures of earnings quality changed over time? *Journal of Accounting and Economics*, 57(2):196 – 217.

Starica, C. and Marton, J. (2020). Assessing the price-earnings association in the age of machine learning. Technical report, Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3813048.

Stock, J. H. and Watson, M. W. (2012). *Introduction to Econometrics*. Addison-Wesley.