The Stock Market Valuation of Human Capital Creation

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Abstract

We develop a measure of firm-year-specific human capital investment from publicly disclosed personnel expenses (PE) and examine the stock market valuation of this investment. Measuring the future value of PE ($PEFV$) based on the relation between lagged PE and current operating income, we first show that $PEFV$ is positively associated with characteristics of human-capital-intensive firms. Next, we find that $PEFV$ has a positive pricing coefficient, implying that the market recognizes some of its variation. In our main analysis, we find that market participants fail to fully impound the investment in human capital. The absolute value of analyst forecast errors is increasing in firm $PEFV$, and the signed value of these errors reveals that analysts are pessimistic for earnings of firms with high human capital investments. A long-short portfolio based on $PEFV$ produces annualized value-weighted (equal-weighted) abnormal returns of 6.5% (3.5%). Portfolios formed by interacting $PEFV$ with total PE, which combines the current potential investment in human capital with the historic portion of PE that created human capital, increase these returns to between 4.8% and 7.8%. These results are insensitive to numerous empirical choices.

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1 Introduction

Accounting rules require that most expenditures related to employees be treated as costs and expensed as incurred. The reason for this treatment is that unlike with assets, firms do not have control over their employees (i.e., employees are not forced to remain employed by the firm). Still, costs related to employees likely consist of two components, the immediate expense that ensures that employees contribute to maintaining current business operations, and the investment that encourages employees to improve in their roles and grow the firm. This latter component, which can take various forms ranging from incentive-based compensation to on-the-job training, gives rise to the trope illustrated by Xerox CEO Anne Mulcahy in 2003 that "Employees are a company's greatest asset."[1]

This paper seeks to better understand the information contained in employee expense disclosures, specifically the "Personnel Expense" (PE) line item that firms are required to disclose under International Financial Reporting Standards (IFRS).[2] To do so, we develop a methodology to identify at the firm-year level how successful a firm is at investing in personnel (i.e., the human capital investment). Our main analysis examines whether market participants recognize and appropriately value this component of PE, what we refer to as the future value of PE, or $PEFV$.

While measuring human capital creation is complex and imperfect, it is growing increasingly important. In a 2000 paper, Luigi Zingales wrote, "The wave of initial public offerings of purely human capital firms... is changing the very nature of the firm" (Zingales, 2000). If anything, the change has accelerated since the time of that writing. As shown in Figure 1, from 1992 to 2018, capital expenditures as a percentage of total sales remained relatively flat at about 10%. On the other hand, PE almost doubled during that

[1]This quotation is attributed to a speech Mulcahy made in May at the Doral Arrowwood Resort in Rye Brook, N.Y.

[2]Throughout the paper we use the terms "personnel expense" or "personnel expenditure" to refer to the Thomson Reuters Datastream item *Personnel expense for all employees and officers* (mnemonic WC01084). This item mostly relates to personnel expenditures that are expensed as incurred. As defined in IAS 19, the item includes, among others, the costs for hiring, wages, salaries and bonuses, social security and insurance costs, perquisites like catering and work wear, and post-termination benefits. While some firms disaggregate expenses by nature so that PE is visible on the income statement, most firms disaggregate by function and provide total PE somewhere in the notes. In the latter case, PE is typically divided among firms' cost of goods sold, selling, general and administrative expense, and research and development expense.

time. By 2018, *PE* consumed more than one third of all of the average firm's revenues in our large sample of publicly traded European firms reporting under IFRS.

The growing importance of human capital to firms' profit generating abilities, combined with the paucity of disclosures related to employees and investment in the workforce, potentially creates an information gap that distorts valuation of the firm (Zingales, 2000). While IFRS requires firms to disclose *PE*, under U.S. Generally Accepted Accounting Principles (GAAP), firms are required to disclose only the total number of employees and, since 2018, the salary of the median employee, a measure that lacks relation to future performance (Rouen, 2020).

Given these limited disclosures, investors face informational challenges when attempting to recognize variation in firms' abilities to effectively invest in intangible assets broadly and generate human capital specifically. Prior research investigates whether markets realize the future value generated by firms' expenditure on input resources such as research and development (R&D) (e.g., Eberhart et al., 2004; Lev and Sougiannis, 1996), advertising (Chan et al., 2001), and selling, general, and administrative (SG&A) (Banker et al., 2019). Moreover, accounting and finance scholars have shown the need for markets' recognition of firms' human capital quality (e.g., Ballester et al., 2002; Edmans, 2011; Lee et al., 2018; Pantzalis and Park, 2009). To provide a better understanding of human capital investments, we analyze the stock market valuation of *PE*, the expenditure of the input resource that is most intuitively related to the ability to create human capital.

Empirically, it is unclear whether and how *PE* should be associated with the future value of the firm. To a large extent, *PE* consists of the wages paid to workers in the period in which that work is done. If intangible human capital investments are absent from (or an insignificant component of) *PE*, then there should be little relation between *PE* and future returns given that the resource is consumed in the period in which it is reported. Alternatively, Bertrand and Mullainathan (2003) suggests that abnormally high *PE* may be due to a failure of governance, with managers paying more than is required to reduce their obligations at a cost to shareholders, meaning that higher *PE* may be associated with lower returns. Lastly, a portion of a firm's *PE* may support current operations as a cost, while another significant portion may constitute a personnel investment to develop human capital for future income (Flamholtz, 1971).

Prior literature has provided suggestive evidence of the usefulness of *PE* for valuation purposes. While expenditures associated with human capital investments are not recognized on firms' balance sheets, total *PE*, as reported on the income statement, has been shown to increase earnings predictability and value relevance (Schiemann and Guenther, 2013; Rouen, 2019). If a meaningful portion of *PE* represents investment in human capital, and human capital accounts for a relevant portion of firms' market values, then these investments, when properly measured, should be predictive of future returns (Ballester et al., 2002). Moreover, *PE* clearly supports employee satisfaction, which correlates with abnormal returns (Edmans, 2011).

Another potential reason why *PE* could be value relevant relates to risk. Human capital creation in general and high *PE* in particular increase firm risk, given that these investments, much like R&D, have uncertain outcomes, and, in a way, may have even greater uncertainty than research investments. Similar to research, investing in employees comes with the risk that the investment might fail due to a misunderstanding of the employees or skill in which the firm invests. In addition, because firms do not own their employees, human capital is reduced when employees leave the firm (Lev and Schwartz, 1971). High *PE* may also be difficult or costly to adjust in the short run, leading to high labor leverage and increasing firms' equity risk (Donangelo et al., 2019; Rosett, 2003), which could lead markets to demand a risk premium. For example, Donangelo et al. (2019) finds that firms with high labor bills have higher expected returns, in part because these firms' operating profits are more sensitive to economic shocks given the stickiness of employee costs.

Our approach differs from prior studies in that we acknowledge that *PE* can impact future earnings (Schiemann and Guenther, 2013), and that there are firms where *PE* constitutes a substantial human capital investment (Ballester et al., 2002), but we capture cross-industry and cross-firm *variation* in the ability to create future value from *PE*. This strategy allows us to explore whether and when the stock market realizes the future value created by PE.

This paper takes several steps to further the nascent literature on the relations among employee expenditures, human capital creation, and firm performance. Adapting methodologies to extract from an expenditure the intangible assets created by that expenditure, we create a proxy for the component of PE consisting of investments in human capital by identifying the relation between prior period PE and current firm performance (e.g., Banker et al., 2019; Chen et al., 2012; Huson et al., 2012; Lev and Sougiannis, 1996). For a large sample of firms across 30 European countries, in our main analyses we begin by regressing at the industry level current operating income on several years of lagged PE to identify the optimal lag structure for each industry in terms of the number of years in which PE influences income after that PE is initially incurred.[3] In some industries, as many as three years of lagged PE are significantly positively associated with current operating income (e.g., manufacturing) while in other industries, prior PE has no relation to current performance (e.g., chemicals). Next, we rerun these regressions at the firm-year level using the industry-determined lag structure. Summing the coefficients on prior PE from these regressions provides a firm-year estimate of the PE future value ($PEFV$), our main variable of interest.

We begin our empirical analysis by validating our proxy for human capital investment ($PEFV$), examining whether $PEFV$ is associated with firm characteristics that are likely to be related to the importance of human capital creation. We find that firms with higher $PEFV$ are smaller, have higher market-to-book ratios, have fewer tangible assets, and provide more training days to employees. That growth and less capital-intensive firms have higher $PEFV$ provides us with confidence in this measure as an effective proxy for investments in human capital.

Next, we examine the association between $PEFV$ and contemporaneous stock price. While the relation between total PE and stock price is negative and significant, the relation between $PEFV$ and contemporaneous price is positive and significant. This result suggests that the stock market, to some extent, differentiates between the current

[3]The optimal lag structure is determined by identifying the number of prior years in which PE has a statistically significant relation with current operating income.

operating expense component of *PE* and the future value of *PE*, which is treated as an intangible asset. In other words, the stock market recognizes at least some of firms' human capital creation at the time when the investment in that human capital materializes (i.e., when the prior period investment is consumed). This result is robust to a battery of different controls and specifications. While *PEFV* is measured with error, these results provide further evidence that *PEFV* captures, in part, the investment we are attempting to measure.

Our main analyses examine whether market participants fully recognize this future value of the intangible asset included in *PE*. To do so, we analyze the predictive power of *PEFV* for sell-side analysts' earnings forecast errors and firms' future stock returns. First, we find a significant positive relation between the magnitude of *PEFV* and forecast errors, as well as absolute forecast errors. These results suggest that, not only do analysts fail to incorporate into their forecasts the full value of the investment component of *PE*, but that they overweight the expense component, resulting in pessimistic forecasts.

Next, we build two types of portfolios based on *PEFV*. First, we sort firms into portfolios based solely on *PEFV*. Second, we sort firms into portfolios based on the combination of *PEFV* and *PE* scaled by total assets, *PEFV*PE/TA*. This second set of analyses provides insights into both the investment in human capital and the opportunity to make that investment, based on the total amount spent on employees in the current period. These portfolio analyses produce statistically and economically meaningful results. A value-weighted (equal-weighted) long-short investment strategy based on the level of *PEFV* returns annualized abnormal returns of 6.5% (3.5%), while a strategy that divides firms into portfolios based on *PEFV*PE/TA* results in abnormal annualized returns of 7.8% (4.8%) in the subsequent year. These results, which are statistically and economically significant, suggest that the market fails to fully impound the human capital development embedded in *PE*, as well as the opportunity to make that investment. The results are also robust to numerous alternative specifications, including assigning portfolios based on industry, excluding firms from countries with illiquid currencies, using different factor models, and requiring identical lag structures across all firms when calculating *PEFV*.

The results also remain unchanged when conducting Fama-MacBeth cross-sectional regressions (Fama and MacBeth, 1973). Lastly, we find that the abnormal portfolio returns decrease monotonically over time, with statistically significant value-weighted returns of 5.1% in the second year after portfolio formation, and insignificant returns of 3.1% in the third year.

Given that $PEFV$ likely fails to include some investment in human capital that did not materialize, we also explore whether the results are robust to an alternative measure of human capital investment that is likely to capture these investments. We adapt Enache and Srivastava (2017) in creating an alternative measure of human capital investment and find that portfolios formed using this measure continue to produce abnormal returns. Still, we acknowledge that our proxy for human capital investment is measured with error. Total personnel expense is an admittedly crude starting point to approximate measures of human capital. Included in PE is not only wages, social security expenses, and training costs, but also costs like uniforms, firm-hosted daycare centers, and meals. Exacerbating the challenge is that firms in our sample do not disaggregate this significant operating expense in any meaningful way. Therefore, the findings in this paper should serve as evidence that disclosures related to human capital are value relevant and can provide a basis for how firms and regulators can improve employee-related disclosures as they become increasingly relevant in the knowledge economy.

This paper makes several contributions to the literature. First, we provide evidence of the value of human-capital-related disclosures to market participants. There is little evidence of the relation between employee expense and future firm performance, and we are the first to develop an effective way to extract the future value of the expenditure from the total expense.[4] We show not only that there is significant variation in the ability of firms to generate future value from their investment in employees through PE, but also that employee expenses are relevant for future performance and mispriced by the market.

Second, we contribute to two ongoing regulatory debates. Our results are informative to U.S. investors and the Securities and Exchange Commission (SEC), which recently

[4]Papers that examine labor expenses' relation to firm market value are Schiemann and Guenther (2013) and Ballester et al. (2002).

passed an amendment to its Regulation S-K requiring firms to provide a description of the importance of their human capital resources to the underlying business. The current requirement gives firms wide latitude in terms of what they define as material human capital information, and large investors continue to engage regulators on which human capital disclosures are value relevant (Human-Capital-Management-Coalition, 2019; Maurer, 2021). Our results provide guidance on the disclosures that are relevant to investors. In addition, the convergence project between the Financial Accounting Standards Board and the International Accounting Standards Board has discussed whether it is more informative to disaggregate costs by their function or by their nature, including a debate as to whether disclosure of nature of expense items like PE should also be mandatory under by-function systems.[5] Our result that the market does not fully recognize the human capital creation implicit in PE supports the need to consider changes in the accounting for input resource expenditures (e.g., Enache and Srivastava, 2017; Lev, 2019).

Finally, we add the nature of expense perspective to the stream of research on the stock market valuation of intangible assets. Prior literature shows that the market misvalues functional expenses like R&D (Chan et al., 1990; Eberhart et al., 2004; Lev and Sougiannis, 1996), advertising (Chan et al., 2001), and SG&A (Banker et al., 2019). Until now, this research has paid little attention to the nature of the expense, broadly, and PE specifically. Relatedly, we expand the emerging literature on the impact of firms' ability to generate future value from input resource expenditures. For instance, scholars have analyzed the effects of executive compensation and cost decisions on market valuations (Banker et al., 2011; Chen et al., 2012; Huson et al., 2012; Banker et al., 2019). These studies limit their evidence to a subset of employees and rely only on evidence for U.S. firms. We examine an intuitive, widely reported input resource that can be analyzed in an IFRS cross-country setting.

The remainder of this paper is organized as follows. Section 2 describes the data used and the research design. Section 3 reports descriptive statistics, and Section 4 describes the main empirical results and robustness analyses. Section 5 concludes the paper.

[5] We refer to the Financial Accounting Standards Board and International Accounting Standards Board Joint Meeting on Primary Financial Statements in June 2018.

2 Research design, data, and variable measurement

2.1 Research setting and sample selection

To test whether the market realizes firms' human capital creation from *PE*, we exploit the mandate to disclose *PE* for firms listed in European Union (EU) countries. Firms listed on an EU regulated market must report according to IFRS, which requires disclosure of *PE*. We include in our sample the current 27 members of the EU as well as the United Kingdom, which left the EU in early 2020. We further add Norway and Switzerland (e.g., Armstrong et al., 2010; Byard et al., 2011). We therefore begin the sample selection with all firms listed in any of these 30 countries.

Panel A of Table 1 shows the sample selection procedure. We consider 11,569 non-financial and non-utilities firms (e.g., He and Narayanamoorthy, 2020) that were active at some point in time during the period 1991 to 2018. For those firms, we obtain Thomson Reuters Datastream data for 124,507 firm-years from 1992 to 2018, which begins one year later since we use average total assets (*TA*) to deflate the financial statement variables.[6] We remove firm-years with missing financial statement items (*TA*, *PE*, operating income (*OI*), and depreciation & amortization), stock-related data (share price and market capitalization), and number of employees. We consider only firm-years with at least \$20 (\$0.5) million in total assets (personnel expenses). We require at least five firms in every SIC-4-industry-year (e.g., Banker et al., 2011; Lev and Sougiannis, 1996).[7] This procedure results in an initial sample of 64,579 firm-years. Based on this sample, we winsorize the financial statement ratio variables yearly at the 1% and 99% level (Banker et al., 2019). We then remove firm-years where less than four years of lagged data are available, which leaves a sample period from 1996 to 2018. Removing FF12-industry-years with less than 15 firms gives the sample of 33,989 firm-years used to obtain the optimal lag

[6] Many countries required the disclosure of *PE* prior to the EU's IFRS adoption in 2005. We neither observe a kink in data availability around 2005, nor in any other year. We therefore begin our sample in 1992, when these data become widely available.

[7] This requirement is needed for the instrumental variable approach that we explain in the next subsection. If there are less than five firms available in the SIC-4-industry-year, we pool the firms on the SIC-3 level, where we again require at least five firms in the industry-year.

structure per FF12-industry.[8] Of that sample, 21,708 firm-years have sufficient lagged data to allow the firm-year-specific calculation of the human capital investment (i.e., the personnel expenditure future value, *PEFV*). In our main analyses, we focus on the firms from industries with at least one lag and positive *PEFV* estimates. The earliest year where a calculation with one lag is possible is 1998. Our final sample contains 11,009 positive *PEFV* firm-years from 1998 to 2018.

Panel B of Table 1 shows the distribution of firm-years among countries and FF12-industries for the 33,989 firm-years used to obtain the optimal lag structure per industry and for the final sample of 11,009 positive *PEFV* firm-years. United Kingdom firms account for the largest portion of firm-years, followed by French and German firms. The relative weight of the sampled countries is comparable with other studies on EU firms (e.g., Armstrong et al., 2010; Byard et al., 2011; Christensen et al., 2013), implying that the required data availability does not distort the sample such that generalization of the results to the universe of EU firms is not warranted. Firms in the Manufacturing, Business Equipment and residual category Other industries account for the largest portion of firm-years. The sample reduction induced by focusing on the firm-years with positive *PEFV* (i.e., from N to N_{final}) distorts neither the country nor the industry distribution.

2.2 Measurement of personnel expenditure future value

We begin our analysis of the human capital investment implicit in *PE* by estimating the long-term effect of lagged *PE* on current operating income following a two-step procedure. First, we obtain the optimal *PE* lag structure for the relation between operating income and *PE* for each FF12-industry using the following equation:

$$OI/TA_{i,t} = \alpha + \sum_{k=0}^{n} \beta_k (PE/TA_{predicted})_{i,t-k} + \gamma log(\#E)_{i,t} + \eta_t + \varepsilon_{i,t}. \qquad (1)$$

Equation (1) is adapted from earlier methodological approaches to be currency neutral (e.g., Banker et al., 2011; Lev and Sougiannis, 1996). We estimate equation (1) for each

[8] We use the Fama and French industry classification as it provides intuitive and consistent categories to assess the industry-specific lag structure. At the same time, we rely on the SIC categorization for those parts of our methodology that require a numerical disaggregation.

FF12-industry with different numbers of lags (different n).[9] $OI/TA_{i,t}$ is operating income before depreciation & amortization and PE (e.g., Banker et al., 2019) deflated by average TA. $(PE/TA_{predicted})_{i,t-k}$ is the predicted value using an instrumental variables approach for the deflated PE of year t-k as follows:

Following Lev and Sougiannis (1996) and Banker et al. (2019), we use industry-year PE as an instrument in equation (1) to address a potential simultaneity problem when a shock to the residual affects both the dependent (OI) and the independent variable (PE).[10] For each firm-year observation, we calculate the average PE of all other firms in the SIC-4-industry ($(PE/TA_{SIC4-i})_{i,t}$). We assume that firm idiosyncratic shocks do not affect industry-year PE.[11] At the same time, industry-year PE should be highly correlated with firm-year PE. For each year and SIC-2-industry, we regress $PE/TA_{i,t}$ on the industry-year PE:

$$PE/TA_{i,t} = \alpha + \beta(PE/TA_{SIC4-i})_{i,t} + \varepsilon_{i,t} \tag{2}$$

We obtain the predicted value $(PE/TA_{predicted})_{i,t}$ from equation (2) and use it in the industry-level and firm-year-level estimations of equation (1).

In equation (1), we include the natural logarithm of the number of employees to account for firm size as there may be scale effects when analyzing how intangible investments are reflected in future income (Ciftci and Cready, 2011) and also include year indicators (η_t).[12] For each FF12-industry, we determine the lag structure with all positive and statistically significant (at the one-sided 10% level) coefficients and the most explanatory

[9]Banker et al. (2019) consider models ranging from zero to seven years, Huson et al. (2012) consider up to five lagged years in their industry-specific analyses of the future value of SG&A. It appears unlikely that rather old human capital is still systematically relevant for operating income. Moreover, Ballester et al. (2002) find that human capital assets depreciate, on average, over three years. Thus, we consider models ranging from zero to four lags of PE in the industry-specific analysis.

[10]For example, demand for a firm's products may increase due to some exogenous shock. This could lead to both an increase in OI and an increase in the returns to input resource expenditure like PE, which would in turn lead to an increase in PE. PE could therefore no longer be treated as an exogenous variable.

[11]The firms in a SIC-4-industry may still be subject to a SIC-4-industry idiosyncratic shock.

[12]Banker et al. (2019) add current R&D and advertising expenditures to the model when estimating the future value of SG&A. PE already contains the personnel expenses included in SG&A, R&D and advertising, so we do not add any of the functional expenditure items to the model.

power.[13]

Second, we fix the optimal lag structure from the first step for all firms of a given industry. We next rerun equation (1) at the firm-year level.[14] For each firm-year, we use current and historical data of that firm, compatible with an investor's information set at a given point in time. We only run the regression in firm-years where there is sufficient historical data to obtain all coefficients of the respective model.[15] We use rolling windows of historical years in the firm-specific regressions using the number of lags determined at the industry level in the first step. $PEFV_{i,t}$ is calculated as the (discounted) sum of the firm-year-specific coefficients on past *PE* ($PEFV_{i,t} = \sum_{k=1}^{n} \beta_k/(1.1)^k$) and serves as the proxy for human capital investment.[16] The intuition is that it reflects the total effect of a currency unit of spending of current *PE* on future *OI*. To allay concerns about measurement error, we show in Section 4.4.4 that our main results are robust to an alternative strategy for measuring human capital investment.

2.3 Optimal lag structure

The first step of the two-step-procedure to estimate *PEFV* is to define the optimal lag structure for each industry by estimating equation (1) at the industry level. To gain initial insight on the impact of past *PE* on current *OI*, we show results for estimating equation (1) *across* industries including FF12-industry indicators in Panel A of Table 2. We show results for structures of one to four lags. The table shows that past streams of *PE* with different lag structures have significantly positive effects on current *OI*. In each of the four models, the discounted coefficients on past *PE* add up to between 0.355 and 0.417. It thus appears that a substantial portion of *PE* is a value-creating investment on

[13]We assess the explanatory power according to the Akaike Information Criterion (AIC), the Schwartz Bayesian Criterion (SBC), and adjusted R^2. We thereby regard a model to have the highest explanatory power when both AIC and SBC are lowest for this model. If the AIC and SBC criterion leave two different models, the model with the higher adjusted R^2 is chosen.

[14]We do not include the proxy for firm size when running the regressions on the firm-year level. Those regressions also do not provide the degrees of freedom to include year indicators.

[15]For instance, for a firm with full data coverage from 1992 to 2018, 1996 is the first year where data of the four preceding years is available. If the firm operates in a FF12-industry where we identify three lags to have the highest explanatory power, then the firm-year-specific regression for this firm has five coefficients (α and β_0 to β_3). This regression is possible from year 2000 onward.

[16]We use the same interest rate of ten percent to discount the coefficients as earlier papers (e.g., Banker et al., 2011, 2019). The results are not sensitive to the choice of the interest rate.

average.

Next, we obtain the optimal lag structure per industry. We run equation (1) industry-by-industry. Panel B of Table 2 provides the coefficient estimates for the lag structure with all positive and significant coefficients and the highest explanatory power for each industry. The optimal number of lags varies substantially from zero to three. Past PE has no impact on current OI in the Chemicals & Allied Products industry. It appears meaningful that the lag structure persists into two or three earlier years in industries like Manufacturing and Healthcare, Medical Equipment, and Drugs, where firms can add relatively high value to the products and services they offer through human capital investments. Consumer-oriented industries like Consumer NonDurables and Wholesale, Retail, and Some Services also seem to have longer lag structures. Overall, the results support the notion that the magnitude of the future values generated by PE varies considerably across industries. In a later section, we apply two or three lags across all industries to allow firms to "compete on equal grounds" and find that our main results remain unchanged.

3 Descriptive statistics

Table 3 shows descriptive statistics for the lag structure variables of equation (1) and for the variables used in the contemporaneous stock price and forecast error analyses. Panel A gives descriptive statistics for the initial sample before requiring four years of lagged data. Measured in U.S. dollars, the mean (median) TA value is \$2,861 million (\$239 million) and the mean (median) PE value is \$417 million (\$52 million). The mean (median) PE scaled by average TA (PE/TA) amounts to 0.27 (0.23). Panel B shows descriptive statistics for the final sample of positive $PEFV$ firm-years. The observations included in this sample are larger in terms of TA and PE compared with the initial sample. We calculate $PEFV_{i,t}$ as the sum of the present values of the coefficients on lagged PE for each firm-year. Focusing on positive $PEFV_{i,t}$ estimates gives a highly right-skewed variable. We therefore winsorize it at the 95% level. The resulting mean value is 2.08, and the median is 1.28, which implies that the total effect of spending of PE on future operating income is larger than its nominal value. Panel B further describes the variables used in the contemporaneous price analyses and the contemporaneous forecast error analyses. All variables are defined in Appendix A.[17]

3.1 *PEFV* and firm characteristics

To assess the plausibility of *PEFV* as a proxy for human capital creation, Table 4 presents evidence of the association between firm characteristics and *PEFV*. We use deciles of *PEFV*, rescaled to range from zero to one for firm-years with a positive *PEFV*. Firms' logged number of employees as a proxy for size or life-cycle is significantly negatively associated with *PEFV*, implying that smaller firms are more likely to generate high future values from their *PE* investments. The significantly positive coefficient on the market-to-book ratio suggests that growth firms have higher *PEFV*. The coefficient for asset tangibility is significantly negative, and the coefficient for current *PE/TA* is significantly positive, which means that firms that are less capital-intensive and more reliant on employees are more effective at investing in human capital. Average pay per employee is significantly positively associated with *PEFV* on a stand-alone basis. When examining all variables in a single model in column (6), our inferences remain unchanged, with the exception of the coefficient on *MeanPay*, which becomes insignificant. Column (7) reports the relation between the average training days per employee and *PEFV* for the small subsample of firms that report this information. Consistent with *PEFV* being a proxy for human capital investment, the coefficient on *TrainingDays* is positive and significant. Overall, these results suggest that firms that are more reliant on labor, faster growing, and less reliant on capital, as well as those that invest more in training, are, on average, more effective at creating human capital, lending credence to the claim that *PEFV* is an intuitive proxy for human capital investment.

[17] All variables are scaled by $P_{i,t-1}$ and winsorized at the 5% and 95% level.

4 Market participants' recognition of human capital creation

Having shown that $PEFV$ is a plausible proxy for firms' human capital investment, we next turn to our main analysis, examining whether stock market participants recognize this investment in a timely manner.

4.1 Contemporaneous stock prices and $\boldsymbol{PEFV}$

In our first market realization analysis, we estimate the association between contemporaneous stock prices and $PEFV$. To do so, we estimate the model from Kothari and Zimmerman (1995) as follows:

$$P_{i,t}/P_{i,t-1} = \alpha + \beta OIPS_{i,t}/P_{i,t-1} + \gamma PEPS_{i,t}/P_{i,t-1} + \delta PEFV_{i,t}/P_{i,t-1} + Controls + \varepsilon_{i,t}, \tag{3}$$

where $P_{i,t}$ is the end of year stock price, $OIPS_{i,t}$ is a per-share measure of OI excluding PE, $PEPS_{i,t}$ is PE per share, and $PEFV_{i,t}$ is the firm-year-specific future value of PE. All variables are converted to U.S. dollars and deflated by the beginning of year stock price to address scale differences. If the future value of human capital investment has a positive impact on contemporaneous price, then we expect a positive coefficient on δ. We expect β to have a positive pricing coefficient. If the contemporaneous stock market values PE's current portion negatively (given that the expense mechanically reduces earnings), γ will be negative.

Table 5 shows the regression results of implementing equation (3). The coefficient on $OIPS_{i,t}/P_{i,t-1}$ is positive and significant in all specifications, indicating a positive relation between OI and contemporaneous stock prices. The coefficient on $PEPS_{i,t}/P_{i,t-1}$ is significantly negative in most specifications, and the coefficient on $PEFV_{i,t}/P_{i,t-1}$ is significantly positive in all specifications. This result indicates that the contemporaneous stock market values PE's current portion negatively and its future value portion positively.

The results support the conjecture that high $PEFV$ (i.e., high human capital investment) is, at least partially, reflected in contemporaneous prices.

In this table and those that follow, we follow Banker et al. (2019) and exclude negative $PEFV$ firm-years from the analysis to mitigate the effect of measurement errors in $PEFV$. We further exclude firm-years from industries with zero lags (i.e., zero $PEFV$) to capture the contemporaneous pricing effect of relative differences in $PEFV$. Comparing columns (1) (which includes all firm-year observations) and (2) (which makes the above exclusions), we find that reducing the sample to include only $PEFV$ values larger than zero does not substantially affect the coefficients on $OIPS_{i,t}/P_{i,t-1}$ and $PEPS_{i,t}/P_{i,t-1}$. Columns (3) and (4) show results for the effect of $PEFV$ without and with the inclusion of industry and year fixed effects. Column (5) shows that the pricing coefficient on $PEFV$ remains significantly positive after we include the contemporaneous analyst forecast for earnings per share. This result suggests that investors make PE-related adjustments to analyst forecasts and do not necessarily take them at face value.

Column (6) shows that the results are robust to the inclusion of SG&A per share as well as R&D per share as in Banker et al. (2019). Column (7) presents results for the inclusion of year and firm indicators as an alternative fixed effects specification. This specification increases the magnitude of the positive pricing coefficient of $PEFV$ (compared with column (5)) and turns the pricing coefficient of current PE insignificant. Finally, in column (8), we consider the deciles measure of $PEFV$ that we use in Table 4 as an alternative, which also has a significantly positive pricing coefficient. The results presented in Table 5 provide strong evidence that investors contemporaneously recognize some of the human capital investment made by firms.[18]

[18] While Banker et al. (2019) find that the future value of SG&A ($SGAFV$) is positively associated with contemporaneous and future returns, due to its required disclosure, PE is more broadly available for IFRS firms than is SG&A. Given that personnel expense is likely to make up a significant portion of SG&A, we examine whether our results are robust to including $SGAFV$ in our analysis for the subset of firms that disclose SG&A, using the methodology described in Section 3. Appendix B shows the results of regressing the contemporaneous price on $SGAFV$ and control variables. Column (1) shows that the calculation of $SGAFV$ is meaningful in the sense that there also is a positive pricing coefficient as in Banker et al. (2019). In column (2), $PEFV$ is included and shows a positive pricing coefficient while the coefficient for $SGAFV$ turns insignificant. This analysis suggests that $PEFV$ is incrementally informative to $SGAFV$ in relation to contemporaneous price changes and further stresses the importance of understanding human capital investment for valuation purposes.

4.2 Analysts' forecast errors and *PEFV*

Next we examine the relation between analysts' earnings forecast errors and *PEFV*. Given that the information contained in *PEFV* is not directly observable and contains uncertainty, as well as the negative mechanical relation between *PE* and earnings, it is plausible that analysts do not correctly forecast earnings when firms invest heavily in human capital. We first look at the relation between *PEFV* and the absolute value of the contemporaneous mean forecast error in a specification similar to the contemporaneous return analysis.

In column (1) of Table 6, we regress the absolute difference between reported earnings per share and the mean analyst consensus forecast on *PEFV*, operating income per share, and *PE* per share, scaled by the beginning of year share price. We add the number of analysts following the firm to control for analysts' attention to the firm, as well as the controls included in the prior analysis. The coefficient on *PEFV* is positive and significant in columns (1) through (3), indicating that analysts are less able to anticipate earnings of firms that invest more in human capital. In column (2), we add controls for the change in operating income and *PE* to capture year-over-year surprises in these measures. We add the change in SG&A and R&D in column (3) and continue to find the positive effect for *PEFV*. We repeat those analyses using signed forecast errors in columns (4) through (6). Finally, in column (7), we show that we get similar results when using the alternative *PEFV* deciles measure. Taken together, these results indicate that analysts do not fully incorporate investment in human capital into their forecasts, and that they are, on average, pessimistic in their forecasts, possibly because human capital investments are not directly disclosed but mechanically reduce earnings in the current period due to the expensing of *PE*.

4.3 Future portfolio returns

Having established that markets put a positive contemporaneous pricing coefficient on high human capital creation and that analysts seem to underestimate its influence on earnings, we investigate the effect of human capital investment on firms' future returns.

To do so, we conduct future portfolio returns analyses where the portfolios are formed based on human capital investment (*PEFV*). Our main results are based on the five-factor model (Fama and French, 2015) as follows:

$$\begin{aligned} R_{p,\tau} - R_{f,\tau} = \alpha + \beta_{market}(R_{m,\tau} - R_{f,\tau}) + \beta_{size} SMB_\tau + \\ \beta_{value} HML_\tau + \beta_{profit} RMW_\tau + \beta_{invest} CMA_\tau + \varepsilon_{p,\tau}. \end{aligned} \tag{4}$$

This model consists of the three factors for general market risk, firm size, and value-growth plus two additional factors for operating profitability robustness and investment aggressiveness (Fama and French, 1993, 2015).[19] We form the portfolios at the end of June of year *t+1*, assuming that year *t*'s fiscal results are disseminated by then. We calculate equal- and value-weighted monthly returns on the portfolios ($R_{p,\tau} - R_{f,\tau}$) for the subsequent twelve months, i.e., from July of year *t+1* to June of year *t+2* (e.g., Fama and French, 1992).[20]

The variable of interest in equation (4) is the intercept α which measures the abnormal return. If stock market participants fail to fully incorporate the impact of human capital investment on future performance, then α will increase with portfolios built from higher quintiles (i.e., those with greater human capital investment). $R_{p,\tau}$ is the return on portfolio p in month τ. The coefficient on $R_{m,\tau} - R_{f,\tau}$ captures the portfolio's exposure to the general market risk premium over the risk-free interest rate with $R_{m,\tau}$ being the value-weighted market return and $R_{f,\tau}$ being the rate of the one-month Treasury bill. The coefficient on SMB_τ measures exposure to the size premium. The coefficient on HML_τ measures association with the value-growth factor where portfolios are built with book-to-market quantiles. The coefficient on RMW_τ captures exposure to a factor that measures robustness of firms' operating profitability. Finally, the coefficient on CMA_τ estimates the association with the investment aggressiveness factor.

We form portfolios based on two measures for the future intangible asset value of *PE*: *PEFV* and *PEFV*PE/TA* (Banker et al., 2019). The latter interacts *PEFV* with

[19] We obtain all data for the factor returns from the monthly European five-factor files on Kenneth French's data library (French, 2019).

[20] The factor returns take the perspective of a U.S. investor, thus we measure all returns in U.S. dollar (e.g., Fama and French, 2017). We obtain monthly stock-related Thomson Reuters Datastream items for these analyses.

current *PE* (*PEFV*PE/TA*) to implicitly combine the historically estimated intangible asset investment with the current opportunity set, where *PE* is the proxy for opportunity. *PEFV*PE/TA* is similar to the measure of capitalized R&D used in Chan et al. (2001) in that it creates a proxy for an intangible asset that depreciates over time. Since the portfolio analyses are supposed to capture abnormal return variation dependent on the variation in *PEFV*, we rely on the sample of firm-years with *PEFV* larger than zero (11,009 observations) to create these portfolios.[21]

Table 7 reports the results for the main quintile portfolio analyses in the 12 months after portfolio formation. Panel A shows value-weighted returns for both *PEFV* and *PEFV*PE/TA* and Panel B shows equal-weighted returns. In all specifications, the abnormal returns after controlling for the risk factor model are negative for the first quintile portfolios and significantly positive for the fifth quintile. The long-short returns are statistically and economically significant in all specifications. The annualized long-short value-weighted (equal-weighted) returns are 6.5% (3.5%) for *PEFV* and 7.8% (4.8%) for *PEFV*PE/TA*. The pattern of exposure to the risk factors indicates that high human capital creation firms are smaller and are growth (rather than value) firms with less robust profitability and more aggressive investments.[22] These results provide evidence that the market does not fully capture firms' variation in human capital creation, and this failure to impound the impact of human capital is strongest when examining the combination of the historic human capital investment and the opportunity to invest in human capital.

4.4 Additional analyses

4.4.1 Alternative portfolio formations and measures of abnormal returns

Our methodology to measure the human capital creation is FF12-industry-specific regarding the optimal lag structure. However, we build the portfolios by sorting the firms

[21]We build the portfolios for the first time at the end of June 2000, such that we have a minimum of 40 firms per portfolio. Accordingly, we have 228 months in the portfolio analyses from July 2000 to June 2019.

[22]There is a strong pattern of lower exposure to the value factor for higher quintiles, with even strongly negative exposure to the factor for high quintiles when value-weighting the returns. This is in line with portfolio results for firms with high employee satisfaction reported by Edmans (2011). We remove the value factor from the model in the next table.

across all industries. As a primary robustness analysis, we follow Eisfeldt and Papanikolaou (2013) and build the portfolios per industry. Panel A of Table 8 shows the results for value-weighted *PEFV*PE/TA* portfolios.[23] We continue to get significant abnormal returns, but the magnitude is smaller than before.

Further, our sample consists of firms from countries with many different currencies, all of which are converted so that the analysis takes the perspective of an investor denominating returns in U.S. dollars. Some of these currencies (i.e., the Hungarian Forinth) are illiquid, which may lead to strong fluctuations in the exchange rate between the respective currency and the dollar. Such strong fluctuations may have an impact on the return measurement, impacting the results of the portfolio analyses. To mitigate this concern, we reduce the sample to firms from countries with highly liquid traded currencies (i.e., the Euro and the British Pound) and redo the portfolio formation with this subsample of firms.[24] Panel B of Table 8 shows that we find even stronger abnormal returns when doing so. In untabulated results, we also find stronger results when we remove penny stocks from the portfolios before calculating the returns as in Cohen et al. (2013).

The five-factor model that we use in our main analysis should be most suitable to analyze the risk return profile of portfolios based on an investment characteristic like human capital. It is intuitive that this produces negative long-short exposure to HML_τ, RMW_τ, and CMA_τ. Nevertheless, we remove HML_τ in Panel C and continue to find significant abnormal returns. Furthermore, our main model does not control for momentum in stock returns. We therefore corroborate our findings with a six factor model that adds the momentum factor (MOM_τ) to the main model in Panel D.

Finally, we disregard the optimal lag structure per industry and apply the same number of lags to firms across all industries. This allows firms from all industries to compete for high *PEFV* on equal grounds. We consider two and three lags and present results for the portfolio returns in Panel E and Panel F. We still get significant long-short returns for

[23] As Table 7 shows, value-weighted *PEFV*PE/TA* portfolios generally produce stronger returns. We focus on this specification in the robustness analyses. We get similar but mostly weaker results when equal-weighting the returns or looking at *PEFV* only.

[24] In this analysis we focus on firms from the U.K. (British Pound) and from the countries that adopted the Euro in 1999, i.e., Austria, Belgium, Germany, Finland, France, Ireland, Italy, Luxembourg, Portugal, Spain and The Netherlands.

both the two- and three-lags specifications. Future research may consider the three lag model as a viable alternative to the industry-specific optimality.

4.4.2 Long-term portfolio returns

To further investigate duration and persistence of the abnormal returns, we analyze portfolio returns up to three years after portfolio formation. In Table 9, we observe that the sort on *PEFV*PE/TA* still produces abnormal long-short returns in the second year after portfolio formation of 5.1%, down from 7.8% in the first year. The returns eventually turn insignificant in the third year (3.1%). Untabulated results for *PEFV* show that the annualized figures evolve from 6.5% to 4.6% to insignificant 1.2%. *PEFV* estimates firms' (historic) investment in human capital. It appears meaningful that sorting on this variation leads to abnormal returns in the earlier years after a high investment and decreases in later years.[25]

4.4.3 Cross-sectional future returns

In our main tests, we report abnormal returns in line with standard approaches in the accounting and finance literature. However, portfolio models do not control for other effects on returns, such as firm-specific momentum, accruals, and other investment characteristics. We corroborate our findings with analyses of cross-sectional future returns. Table 10 reports that monthly returns for the one-year-ahead period, using Fama-Macbeth regressions, are statistically significant and positively associated with our measures of human capital creation even after controlling for R&D and SG&A, and when analyzing returns in excess of the industry-mean return (Fama and MacBeth, 1973).

4.4.4 Alternative approach to capture human capital creation

PEFV, the study's main measure of human capital creation implicit in *PE*, identifies firms that generate more future benefits from investing in their personnel. To this end, our

[25]Untabulated results show strong persistence for a simple sort on *PE/TA* where the magnitude stays rather stable in the three years after measurement. As *PE/TA* is strongly auto-correlated, these results indicate that this measure might be a proxy for some systematic risk characteristic that is not captured by the five factor model. We leave this conjecture for future research.

measure commingles measuring how much firms engage in *ex ante* uncertain investments in personnel with how well this investment turns into benefits. An alternative approach would be to restrict the analysis to the *ex ante* investment to also include investment that was initially intended to, but ultimately did not produce future benefits (Kanodia et al., 2004). To show that our results are not sensitive to potential measurement bias inherent in *PEFV*, we adapt the methodology developed by Enache and Srivastava (2017) to our personnel expense setting, employing the following regressions:

$$PE/TA_{i,t} = \alpha + \beta_1 Sales/TA_{i,t} + \beta_2 SalesDecrease_{i,t} + \beta_3 Loss_{i,t} + \varepsilon_{i,t}, \tag{5}$$

and

$$PEInvest_{i,t} = PE/TA_{i,t} - \beta_{1,Ind,t} Sales/TA_{i,t}. \tag{6}$$

Using regression (5), we regress firms' total personnel expenditure on total sales scaled by average total asset, which is a proxy for current output, per industry and year. We also include dummies for firm-years with decreases in sales and negative earnings. We then use the industry-year-specific betas to subtract the portion of *PE* that supports current operations (i.e., the portion that varies with current sales) from total *PE*, leaving the portion of *PE* that should generate benefits in future periods ("*PEInvest*" in equation (6)). As before, we build portfolios around *PEInvest* in June of year *t+1* and measure abnormal returns after controlling for the five factor model from July of year *t+1* to June of year *t+2*. Table 11 shows economically and statistically significant abnormal returns (5.8%) when assigning portfolios cross-sectionally (Panel A) and statistically insignificant returns (3.0%) when assigning portfolios per industry (Panel B).[26] Interestingly, in untabulated results, we find that the abnormal returns for this approach increase in the second year after portfolio formation (i.e., 6.4% and 5.6% for the two approaches) which is different from the pattern in Table 9. This is in line with *PEInvest* serving as a proxy

[26]For these analyses, we use our initial sample of 64,579 firm-years before requiring data availability in previous years. In line with our main methodology, we run the industry-year-specific models on the FF12-industry-level. Accordingly, we build the portfolios within FF12-industries in Panel B. We obtain similar results when we use FF48-industries as in (Enache and Srivastava, 2017). As *PEInvest* can be negative for some firm-years, we also obtain similar results when focusing on the positive firm-years in line with our main methodology.

for initial investment in human capital, whereas $PEFV$ already captures the efficacy of that investment.

5 Conclusion

We develop a strategy to examine aspects of the intangible human capital investment embedded in a firm's personnel expense. We find that our proxy for human capital investment efficacy, $PEFV$, is positively associated with firm characteristics, such as growth opportunities and size, consistent with investment in the construct we seek to measure. Still, disclosures around human capital are limited and opaque. Given the magnitude of the underlying expenditure, we explore whether this opacity hinders price discovery. We show that the contemporaneous stock market prices PE's current portion negatively and its future value portion positively. We next document that risk-adjusted abnormal returns can be earned on portfolios formed on two aspects of the future intangible asset value of PE: the component of PE most likely to represent an investment in human capital, and that component interacted with the opportunity set of potential human capital investment. These findings are robust to model selection and measurement choice.

Our findings are potentially informative to regulators examining how to improve disclosures around human capital. In addition, these insights on the future value generating ability of PE lead to questions for future research: Does the legal environment affect how returns to human capital creation are realized (e.g., Shleifer and Vishny, 1997)? Can firms acquire the human capital creating ability of target firms, and does it matter whether merging firms' human capital creating abilities are related (Lee et al., 2018)? Moreover, there are opportunities for research in other contexts. Does PE have higher cost stickiness when there is a higher potential to create future values from it (Chen et al., 2012)? Do firms with high human capital creating ability grant more long-term executive compensation incentives (Banker et al., 2011), and is executive compensation shielded from the negative effects of expensing personnel expenditures when they create higher future values (Huson et al., 2012)?

Appendix A - Variable definitions

Variable	Definition and Thomson Reuters Datastream mnemonic
$TA_{i,t}$	Average of beginning ($t-1$) and end of year (t) total assets (WC02999)
$PE_{i,t}$	Personnel expense for all employees and officers (WC01084)
$OI_{i,t}^{BDNAPE}$	Operating income (WC01250) before depreciation & amortization (WC01151) and PE used in optimal lag structure and future value regressions
$OI_{i,t}^{BPE}$	Operating income before PE used in contemporaneous price analyses
$PE/TA_{i,t}$	$PE_{i,t}$ scaled by average total assets before instrumental variable approach
$(PE/TA_{predicted})_{i,t}$	Value predicted through instrumental variable approach
$OI/TA_{i,t}$	$OI_{i,t}^{BDNAPE}$ scaled by average total assets
$\#E_{i,t}$	End of year number of employees (WC07011)
$PEFV_{i,t}$	The personnel expenditure future value, which is the firm-year-specific sum of the discounted coefficients on lagged PE
$PEFV-Decile_{i,t}$	Deciles of $PEFV_{i,t}$ scaled to range from zero to one
$PEFV*PE/TA_{i,t}$	$PEFV_{i,t}$ multiplied with $PE/TA_{i,t}$ used in portfolio analyses
suffix $-PS_{i,t}$	End of year shares outstanding (indirect calculation dividing market capitalization (WC08001) by share price (P))
$OIPS_{i,t}$	$OI_{i,t}^{BPE}$ divided by shares outstanding (in US$)
$PEPS_{i,t}$	$PE_{i,t}$ divided by shares outstanding (in US$)
$RNDPS_{i,t}$	R&D expenses (WC01201, set to zero if missing) per share (in US$)
$SGAPS_{i,t}$	SG&A expenses (WC01101) excluding R&D per share (in US$)
$P_{i,t}$	End of year stock price (P, in US$)
$EPS_{i,t}$	Mean consensus earnings per share forecast (EPS1MN, in US$)
$FE_{i,t}$	Actual earnings per share (EPSIBES, in US$) minus mean consensus earnings per share forecast, also used in absolute terms ($|FE_{i,t}|$)
$MTB_{i,t}$	End of year market-to-book ratio (MTBV)
$Tangibility_{i,t}$	End of year property, plant & equipment (WC02501) scaled by total assets
$MeanPay_{i,t}$	PE (in US$) divided by number of employees
$TrainingDays_{i,t}(\%)$	Employee training hours (SOTDDP018) divided by 8 (hours) and 230 (working days) multiplied by 100
$R_{i,\tau}$	Firm-level return in month τ (obtained with mnemonic RI, in US$)
$R_{p,\tau}$	Return of portfolio p in month τ
$R_{f,\tau}$ and $R_{m,\tau}$	Monthly risk-free and market return (from K. French's library)
SMB_τ, HML_τ, RMW_τ, CMA_τ, and MOM_τ	Monthly size, value, operating profitability, investment aggressiveness, and momentum factor return (from K. French's library)
$R_{Ind,\tau}$	Average industry-level (FF12) return in month τ
$Momentum$	Momentum for each month τ, measured as the cumulative return from $\tau-1$ to τ ($Momentum_{-1,0}$) and $\tau-12$ to $\tau-2$ ($Momentum_{-12,-2}$), respectively
$Accruals_{i,t}$	Accruals measured as net income (WC01651) less net cash from operations (WC04860) scaled by book equity (total assets - total liabilities (WC02003))
$AssetGrowth_{i,t}$	Change in total assets from $t-1$ to t scaled by $t-1$
$log(BE/ME)_{i,t}$	Natural logarithm of book equity divided by market capitalization
$log(ME)_{i,t}$	Natural logarithm of market capitalization (MV) as of June $t+1$ (in US$)
$EBITDA/TA_{i,t}$	EBITDA (WC18198) scaled by average total assets

Appendix B - *SGAFV* robustness analysis

	Dependent variable:			
	$P_{i,t}/P_{i,t-1}$			
	(1)	(2)	(3)	(4)
$OIPS_{i,t}/P_{i,t-1}$	0.147	0.153	0.153	0.158
	(0.152)	(0.154)	(0.146)	(0.148)
$PEPS_{i,t}/P_{i,t-1}$	−0.043	−0.056	−0.139	−0.146
	(0.155)	(0.155)	(0.140)	(0.141)
PEFV i,t/P i,t-1		**0.058*****		**0.051****
		(0.022)		**(0.022)**
SGAFV i,t/P i,t-1	**0.100***	**0.025**	**0.086**	**0.022**
	(0.054)	**(0.041)**	**(0.053)**	**(0.041)**
$EPS_{i,t}/P_{i,t-1}$	2.226***	2.237***	2.325***	2.332***
	(0.292)	(0.293)	(0.268)	(0.270)
$SGAPS_{i,t}/P_{i,t-1}$			0.123***	0.117***
			(0.042)	(0.040)
$RNDPS_{i,t}/P_{i,t-1}$			1.748***	1.703***
			(0.576)	(0.574)
Intercept	0.699***	0.685***	0.694***	0.682***
	(0.056)	(0.058)	(0.056)	(0.058)
F12 dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Observations	2,793	2,793	2,793	2,793
Adjusted R^2	0.382	0.385	0.394	0.397

This table reports the results of OLS regression of contemporaneous stock price on *PEFV* and *SGAFV* to test whether *PEFV* is incremental to *SGAFV*. Two-way-cluster robust standard errors, clustering at the firm and year levels, are shown in parentheses. *, **, *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

We calculate *SGAFV* for firm-years within our sample of *PEFV* firm-years with sufficient SG&A data. We use the same instrumental variables approach as in our *PEFV* calculation. We further use the same optimal lag structure on the FF12-industry-level. For the regressions in this table, we focus on the firm-years where both *PEFV* and *SGAFV* are larger than zero.

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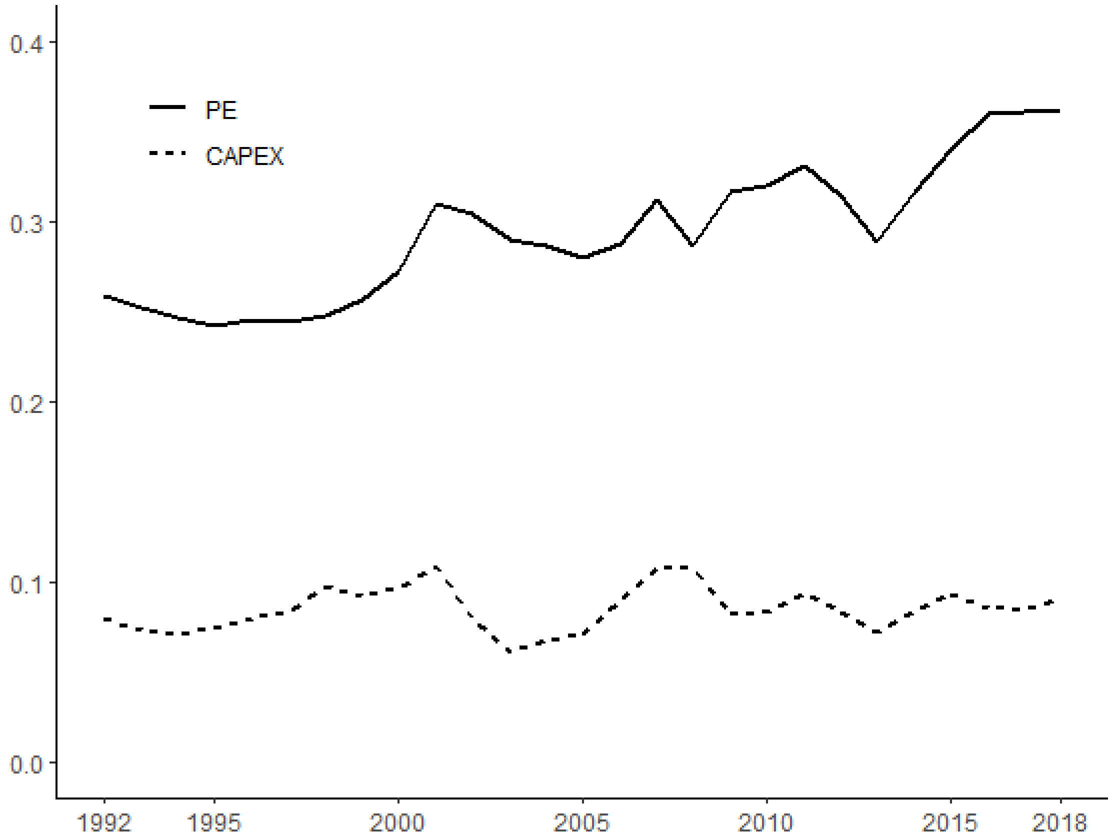
Figure 1: Development of personnel expenditure and capital expenditure over time



This figure plots the annual average personnel expenditure (solid line) and capital expenditure (dashed line) scaled by total sales over the sample period from 1992 to 2018.

Table 1: Sample selection and distribution

Panel A: Sample selection procedure

Selection step	Firms	Firm-years
Thomson Reuters Datastream annual data from 1992 to 2018 for non-financial/non-utilities firms from 30 countries	11,569	124,507
− firm-years with missing financial statement items, stock-related data and number of employees	(2,176)	(39,351)
− firm-years with total assets below 20 million US$ and personnel expenses below 0.5 million US$	(1,202)	(10,740)
− SIC-4-industry-years with less then five firms	(649)	(9,837)
Sample used to winsorize yearly and to estimate $(PE/TA_{predicted})_{i,t}$ with the instrumental variable approach	7,542	64,579
− firm-years with missing data in any of the preceding four years	(3,034)	(30,561)
− FF12-industry-years with less than 15 firms	(3)	(29)
Sample for estimation of optimal lag structure for each FF12-industry from 1996 to 2018 (N in Panel B below)	4,505	33,989
− firm-years with not sufficient data for firm-year-specific regressions	(1,549)	(12,281)
Sample for estimation of PEFV per firm-year	2,956	21,708
− firm-years with negative PEFV	(472)	(9,638)
− firms from industries with zero lags (zero PEFV)	(130)	(1,061)
Final sample with positive PEFV per firm-year from 1998 to 2018 (N_{final})	2,354	11,009
− firm-years with missing earnings per share forecast	(431)	(2,183)
Subsample with forecast data availability from 1998 to 2018	1,923	8,826
− firm-years with missing forecast data to calculate forecast errors	(28)	(154)
Subsample with forecast error data availability from 1998 to 2018	1,895	8,672

Panel B: Firm-year distribution among countries and FF12-industries

Country	N	N_{final}	FF12-industry	N	N_{final}
Austria	595	208	(1) Consumer NonDurables	3,757	1,328
Belgium	805	234	(2) Consumer Durables	1,412	557
Denmark	1,072	333	(3) Manufacturing	6,659	1,944
Finland	1,186	441	(4) Oil, Gas, & Coal Extract. & Products	1,044	411
France	5,226	1,780	(5) Chemicals & Allied Products	1,221	-
Germany	4,723	1,492	(6) Business Equipment	5,371	1,991
Greece	401	70	(7) Telephone & Television Transmission	1,017	434
Hungary	121	57	(8) Utilities (excluded)	-	-
Ireland	474	171	(9) Wholesale, Retail, & Some Services	3,949	1,102
Italy	1,781	595	(10) Healthc., Medical Equipm., & Drugs	1,613	517
Luxembourg	121	44	(11) Finance (excluded)	-	-
The Netherlands	1,373	455	(12) Other	7,946	2,725
Poland	756	164	Total	33,989	11,009
Portugal	501	194			
Spain	1,152	420			
Sweden	1,679	567			
United Kingdom	8,692	2,851			
Switzerland	1,820	562			
Norway	962	281			
Others (BG, CY, CZ, EE, HR, LT, LV, MT, RO, SI, SK)	549	90			
Total	33,989	11,009			

Table 2: Lag structure regressions

Panel A: Cross-sectional regressions with different lag structures

	Dependent variable:			
	$OI/TA_{i,t}$			
	(1)	(2)	(3)	(4)
$(PE/TA_{predicted})_{i,t}$	0.664***	0.609***	0.566***	0.552***
	(0.038)	(0.039)	(0.039)	(0.038)
$(PE/TA_{predicted})_{i,t-1}$	0.391***	0.164***	0.148***	0.113**
	(0.037)	(0.046)	(0.045)	(0.046)
$(PE/TA_{predicted})_{i,t-2}$		0.296***	0.096**	0.079*
		(0.039)	(0.046)	(0.045)
$(PE/TA_{predicted})_{i,t-3}$			0.271***	0.079*
			(0.039)	(0.044)
$(PE/TA_{predicted})_{i,t-4}$				0.270***
				(0.037)
$log(\#E)_{i,t}$	0.016***	0.016***	0.016***	0.016***
	(0.001)	(0.001)	(0.001)	(0.001)
$Intercept$	−0.034***	−0.037***	−0.038***	−0.043***
	(0.009)	(0.009)	(0.009)	(0.009)
$\sum_{k=1}^{n} \beta_k/(1.1)^k$	0.355	0.394	0.417	0.412
Year dummies	Yes	Yes	Yes	Yes
FF12 dummies	Yes	Yes	Yes	Yes
Robust SEs	Yes	Yes	Yes	Yes
AIC	-14286	-14366	-14435	-14508
BIC	-13983	-14054	-14114	-14179
Observations	33,989	33,989	33,989	33,989
Adjusted R^2	0.355	0.357	0.358	0.360

Panel B: Optimal lag structure per FF12-industry

FF12-industry	β_0	β_1	β_2	β_3	$\sum_{k=1}^{n} \beta_k/(1.1)^k$	$R^2_{adj.}$
(1) Consumer NonDurables	.586	.179	.274		.390	.176
(2) Consumer Durables	.957	.578			.526	.114
(3) Manufacturing	.455	.259	.122	.289	.554	.214
(4) Oil, Gas, & Coal Extract. & Products	.310	.451			.410	.260
(5) Chemicals & Allied Products	.833				-	.120
(6) Business Equipment	.517	.524			.477	.209
(7) Telephone & Television Transmission	.623	.612			.556	.015
(8) Utilities (excluded)	-	-	-	-	-	-
(9) Wholesale, Retail, & Some Services	.614	.139	.186	.292	.499	.330
(10) Healthc., Medical Equipm., & Drugs	.554	.499	.295		.697	.299
(11) Finance (excluded)	-	-	-	-	-	-
(12) Other	.643	.136	.248		.328	.415

This table shows the derivation of the optimal lag structure per industry. Panel A reports results of cross-sectional regressions for different lag structures following equation (1). All variables are defined in Appendix A. Columns (1) to (4) present results for one to four lags. Coefficients on industry dummies are not reported. Robust standard errors are shown in parentheses. *, **, *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively. Panel B reports the optimal lag structure per industry where equation (1) is estimated industry-by-industry including year dummies for lag structures of zero to four lags. Only lag structures where all coefficients are positive and significant on the one-sided ten percent level are considered for the choice of the optimal model. The table reports coefficient estimates for the lag structure with the highest explanatory power for each FF12-industry. The last two columns report the discounted sum of the coefficients for the respective optimal lags and the adjusted R^2.

Table 3: Descriptive statistics

Panel A: Characteristics of sample firms from 1992 to 2018

	N	Mean	STD	Min	25%	Median	75%	Max
$TA_{i,t}(\$m)$	64,579	2,861	13,615	20	80	239	998	397,812
$PE_{i,t}(\$m)$	64,579	417	1,524	0.5	17	52	197	40,950
$PE/TA_{i,t}$	64,579	0.27	0.21	0.01	0.13	0.23	0.36	1.33
$(PE/TA_{predicted})_{i,t}$	64,579	0.27	0.13	−0.30	0.18	0.26	0.34	1.28
$OI/TA_{i,t}$	64,579	0.37	0.25	−0.25	0.21	0.33	0.49	1.57
$PE/SALES_{i,t}$	64,579	0.30	0.36	0.02	0.15	0.24	0.34	6.08
$CAPEX/SALES_{i,t}$	63,794	0.09	0.19	0.00	0.02	0.04	0.07	1.98

Panel B: Descriptive statistics of final sample with positive *PEFV*

	N	Mean	STD	Min	25%	Median	75%	Max
$TA_{i,t}(\$m)$	11,009	5,540	21,649	20	177	517	2,459	396,812
$PE_{i,t}(\$m)$	11,009	729	2,089	0.5	43	120	449	38,762
$PEFV_{i,t}$	11,009	2.08	2.04	0.00	0.50	1.28	3.03	6.51
$PE/TA_{i,t}$	11,009	0.28	0.22	0.01	0.13	0.23	0.36	1.33
$PEFV * PE/TA_{i,t}$	11,009	0.49	0.53	0.00	0.09	0.26	0.75	1.64
$P_{i,t}/P_{i,t-1}$	11,009	1.09	0.47	0.07	0.81	1.04	1.30	5.32
$OIPS_{i,t}/P_{i,t-1}$	11,009	0.63	0.57	0.07	0.22	0.43	0.84	2.19
$PEPS_{i,t}/P_{i,t-1}$	11,009	0.56	0.56	0.05	0.16	0.35	0.76	2.09
$PEFV_{i,t}/P_{i,t-1}$	11,009	0.48	0.70	0.00	0.03	0.12	0.56	2.21
$EPS_{i,t}/P_{i,t-1}$	8,826	0.07	0.05	−0.06	0.04	0.07	0.10	0.18
$SGAPS_{i,t}/P_{i,t-1}$	7,164	0.44	0.45	0.03	0.12	0.27	0.57	1.70
$RNDPS_{i,t}/P_{i,t-1}$	11,009	0.02	0.03	0.00	0.00	0.00	0.01	0.13
$\|FE_{i,t}\|/P_{i,t-1}$	8,672	0.04	0.10	0.00	0.01	0.01	0.04	1.46
$FE_{i,t}/P_{i,t-1}$	8,672	0.01	0.10	−0.40	−0.02	−0.004	0.01	1.30
$\#Analysts_{i,t}$	8,672	8.22	7.81	1	2	5	12	44

This table reports descriptive statistics for different samples. Panel A reports characteristics for the initial sample of firms from 1992 to 2018 and Panel B reports descriptive statistics for the final sample with positive *PEFV*.

Table 4: Firm characteristics and $PEFV$

	Dependent variable:						
	$PEFV - Decile_{i,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$log(\#E)_{i,t}$	-0.029^{***}					-0.030^{***}	-0.035^{***}
	(0.002)					(0.002)	(0.010)
$MTB_{i,t}$		0.006^{***}				0.007^{***}	
		(0.002)				(0.002)	
$Tangibility_{i,t}$			-0.059^{***}			-0.037	
			(0.022)			(0.023)	
$PE/TA_{i,t}$				0.076^{***}		0.080^{***}	
				(0.023)		(0.024)	
$MeanPay_{i,t}$					0.001^{***}	0.00004	
					(0.0001)	(0.0001)	
$TrainingDays_{i,t}(\%)$							0.020^{*}
							(0.012)
$Intercept$	0.891^{***}	0.629^{***}	0.670^{***}	0.633^{***}	0.630^{***}	0.872^{***}	0.838^{***}
	(0.031)	(0.019)	(0.021)	(0.018)	(0.016)	(0.033)	(0.094)
FF12 dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,009	10,627	11,008	11,009	11,009	10,626	1,013
Adjusted R^2	0.089	0.060	0.059	0.060	0.062	0.097	0.133

This table reports the results of OLS regression of $PEFV - Decile_{i,t}$ on human-capital-related firm characteristics. All variables are defined in Appendix A. Industry and year dummies are not shown. Two-way-cluster robust standard errors, clustering at the firm and year levels, are shown in parentheses. *, **, *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 5: *PEFV* and contemporaneous stock prices

	Dependent variable:							
	$P_{i,t}/P_{i,t-1}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$OIPS_{i,t}/P_{i,t-1}$	0.735***	0.712***	0.717***	0.631***	0.332***	0.397***	0.461***	0.336***
	(0.058)	(0.058)	(0.059)	(0.051)	(0.073)	(0.095)	(0.096)	(0.074)
$PEPS_{i,t}/P_{i,t-1}$	−0.532***	−0.506***	−0.521***	−0.518***	−0.236***	−0.330***	−0.049	−0.230***
	(0.042)	(0.057)	(0.056)	(0.045)	(0.073)	(0.099)	(0.118)	(0.073)
$\boldsymbol{PEFV_{i,t}/P_{i,t-1}}$			**0.055****	**0.043****	**0.046****	**0.041***	**0.073*****	
			(0.022)	**(0.021)**	**(0.019)**	**(0.022)**	**(0.027)**	
$\boldsymbol{PEFV\text{-}Decile_{i,t}}$								**0.053****
								(0.025)
$EPS_{i,t}/P_{i,t-1}$					2.136***	2.090***	2.767***	2.132***
					(0.242)	(0.259)	(0.376)	(0.242)
$SGAPS_{i,t}/P_{i,t-1}$						0.071***		
						(0.023)		
$RNDPS_{i,t}/P_{i,t-1}$						1.376***		
						(0.322)		
$log(\#E)_{i,t}$	−0.012***	−0.013***	−0.006	−0.005	−0.010**	−0.009*	−0.105***	−0.015***
	(0.003)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.015)	(0.004)
Intercept	1.033***	1.037***	0.962***	1.185***	1.073***	1.024***	2.020***	1.089***
	(0.058)	(0.055)	(0.056)	(0.069)	(0.055)	(0.059)	(0.149)	(0.050)
FF12 dummies				Yes	Yes	Yes		Yes
Year dummies				Yes	Yes	Yes	Yes	Yes
Firm dummies							Yes	
Observations	21,708	11,009	11,009	11,009	8,826	5,960	8,826	8,826
Adjusted R^2	0.097	0.095	0.100	0.341	0.411	0.420	0.491	0.409

This table reports the results of OLS regression of contemporaneous stock price on *PEFV* following equation (3). All variables are defined in Appendix A. Columns (1) and (2) show the sample reduction from all firm-years where *PEFV* is calculated to all firm-years with *PEFV* larger than zero. Column (3) presents the inclusion of *PEFV* and column (4) shows the effect of including industry and year dummies. In columns (5) to (8), the sample is further reduced regarding analyst earnings per share forecast availability. Column (6) presents the inclusion of controls for SG&A per share and R&D per share as in Banker et al. (2019). Column (7) shows results for firm and year dummies. Column (8) shows deciles of *PEFV* rescaled to range from zero to one as an alternative measure. Two-way-cluster robust standard errors, clustering at the firm and year levels, are shown in parentheses. Industry, year and firm dummies are not shown. *, **, *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 6: *PEFV* and contemporaneous forecast errors

	Dependent variable:						
	$\lvert FE_{i,t}\rvert/P_{i,t-1}$			$FE_{i,t}/P_{i,t-1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PEFV $_{i,t}$ ***/P*** $_{i,t-1}$	**0.013***** **(0.002)**	**0.017***** **(0.003)**	**0.015***** **(0.004)**	**0.005**** **(0.002)**	**0.006**** **(0.002)**	**0.006**** **(0.003)**	
PEFV-Decile $_{i,t}$							**0.010***** **(0.003)**
$OIPS_{i,t}/P_{i,t-1}$	−0.175*** (0.033)			−0.205*** (0.031)			
$PEPS_{i,t}/P_{i,t-1}$	0.211*** (0.038)			0.218*** (0.036)			
$\Delta OIPS_{i,t}/P_{i,t-1}$		−0.041 (0.036)	−0.047 (0.033)		−0.081** (0.035)	−0.078** (0.031)	−0.080** (0.035)
$\Delta PEPS_{i,t}/P_{i,t-1}$		−0.052 (0.053)	−0.050 (0.034)		0.017 (0.049)	−0.013 (0.033)	0.015 (0.048)
$\Delta SGAPS_{i,t}/P_{i,t-1}$			−0.018 (0.022)			0.005 (0.023)	
$\Delta RNDPS_{i,t}/P_{i,t-1}$			−0.415*** (0.116)			−0.319** (0.142)	
$log(\#Analysts)_{i,t}$	−0.001 (0.002)	−0.012*** (0.002)	−0.011*** (0.003)	0.001 (0.002)	−0.003 (0.002)	−0.002 (0.002)	−0.004* (0.002)
$log(\#E)_{i,t}$	−0.004*** (0.002)	0.0004 (0.001)	−0.0001 (0.001)	−0.005*** (0.002)	−0.003*** (0.001)	−0.004*** (0.001)	−0.004*** (0.001)
Intercept	0.060*** (0.010)	0.048*** (0.008)	0.059*** (0.010)	0.036*** (0.007)	0.027*** (0.006)	0.029*** (0.010)	0.026*** (0.006)
Observations	8,672	8,672	5,739	8,672	8,672	5,739	8,672
Adjusted R^2	0.158	0.100	0.118	0.113	0.055	0.066	0.055

This table reports the results of OLS regression of contemporaneous forecast errors on *PEFV*. All variables are defined in Appendix A. Absolute forecast errors are the dependent variable in columns (1) to (3). Signed forecast errors are the dependent variable in columns (4) to (7). Column (7) shows deciles of *PEFV* rescaled to range from zero to one as an alternative measure. Two-way-cluster robust standard errors, clustering at the firm and year levels, are shown in parentheses. Industry and year dummies are not shown. *, **, *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 7: Future monthly returns in the year from July to June after portfolio formation

	PEFV						PEFV * PE/TA					
	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}	LS	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}	LS
Panel A: Value-weighted:												
Intercept	−.05	.18	.20	.11	.49***	.54***	−.06	.06	.03	.55***	.59***	.65***
	(.10)	(.12)	(.16)	(.19)	(.14)	(.18)	(.09)	(.12)	(.12)	(.16)	(.18)	(.22)
$R_{m,\tau} - R_{f,\tau}$	1.06***	1.01***	1.06***	1.03***	.97***	−.09*	1.02***	1.02***	1.00***	1.00***	1.06***	.03
	(.03)	(.03)	(.04)	(.05)	(.03)	(.05)	(.03)	(.03)	(.03)	(.04)	(.04)	(.05)
SMB_τ	.15**	.12*	.23***	.12	.002	−.15	.10*	.07	.25***	−.01	.42***	.31***
	(.06)	(.07)	(.09)	(.11)	(.08)	(.10)	(.06)	(.08)	(.07)	(.09)	(.09)	(.11)
HML_τ	−.05	−.10	−.49***	−.45***	−.27***	−.22	−.005	−.06	−.09	−.49***	−.55***	−.54***
	(.10)	(.10)	(.14)	(.17)	(.10)	(.16)	(.10)	(.10)	(.09)	(.10)	(.14)	(.17)
RMW_τ	.15	.08	−.32**	−.17	−.02	−.16	.22**	.06	.02	−.32**	−.17	−.38*
	(.10)	(.11)	(.14)	(.17)	(.13)	(.17)	(.10)	(.09)	(.10)	(.15)	(.15)	(.20)
CMA_τ	.23**	.24**	.26*	−.03	−.02	−.25	.20*	.35***	.28**	−.07	−.03	−.23
	(.11)	(.12)	(.15)	(.19)	(.12)	(.17)	(.11)	(.13)	(.11)	(.14)	(.16)	(.21)
Observations	228	228	228	228	228	228	228	228	228	228	228	228
Adjusted R^2	.92	.91	.84	.81	.88	.09	.93	.90	.89	.85	.84	.20
5^{th}- 1^{st}			**.54*** (.17) Annualized: 6.5%**						**.65*** (.21) Annualized: 7.8%**			
Panel B: Equal-weighted:												
Intercept	−.12	.15	.25***	−.03	.17*	.29***	−.15*	.04	.11	.17*	.25**	.40***
	(.08)	(.10)	(.10)	(.10)	(.10)	(.11)	(.08)	(.09)	(.09)	(.10)	(.11)	(.12)
$R_{m,\tau} - R_{f,\tau}$	1.02***	1.00***	.99***	1.01***	.99***	−.02	1.01***	.98***	.98***	1.05***	1.00***	−.02
	(.02)	(.03)	(.02)	(.02)	(.02)	(.03)	(.02)	(.02)	(.02)	(.02)	(.03)	(.03)
SMB_τ	.78***	.88***	.74***	.91***	.82***	.03	.70***	.84***	.82***	.87***	.92***	.23***
	(.04)	(.04)	(.05)	(.05)	(.05)	(.06)	(.04)	(.04)	(.04)	(.05)	(.06)	(.07)
HML_τ	.27***	.14*	.17**	.25***	.13**	−.13*	.31***	.27***	.20***	.06	.13	−.18**
	(.06)	(.08)	(.07)	(.07)	(.06)	(.07)	(.05)	(.08)	(.06)	(.08)	(.09)	(.08)
RMW_τ	.20***	.10	.01	.19**	.11	−.09	.26***	.14**	.11	.04	.08	−.18*
	(.06)	(.08)	(.08)	(.08)	(.07)	(.09)	(.06)	(.07)	(.07)	(.09)	(.09)	(.10)
CMA_τ	.09	−.02	−.04	−.07	−.08	−.17*	.08	.01	−.09	.01	−.13	−.21*
	(.08)	(.11)	(.08)	(.10)	(.09)	(.09)	(.07)	(.11)	(.09)	(.10)	(.11)	(.11)
Observations	228	228	228	228	228	228	228	228	228	228	228	228
Adjusted R^2	.96	.94	.95	.95	.94	.08	.95	.95	.95	.94	.93	.18
5^{th}- 1^{st}			**.29** (.13) Annualized: 3.5%**						**.40*** (.14) Annualized: 4.8%**			

This table reports monthly abnormal returns of portfolios built around two measures of the future intangible asset value of *PE* following equation (4). All variables are defined in Appendix A. Portfolios are formed at the end of June each year *t+1* by assigning firms into five quintiles based on *PEFV* or *PEFV*PE/TA*. *PEFV* and *PEFV*PE/TA* are measured at firms' fiscal year ending in year *t*. Robust standard errors are shown in parentheses. *, **, *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 8: Robustness analyses regarding portfolio returns

	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}	*LS*
Panel A: Portfolio assignment per FF12-industry						
Intercept	.001	.14	.04	.45**	.36**	.36*
	(.09)	(.15)	(.11)	(.17)	(.16)	(.20)
Observations	228	228	228	228	228	228
Adjusted R^2	.93	.86	.89	.84	.87	.15
5^{th}- 1^{st}	**.36* (.19) Annualized: 4.3%**					
Panel B: Firms from countries with liquid currencies						
Intercept	−.04	−.05	−.08	.41**	.66***	.70***
	(.10)	(.13)	(.13)	(.18)	(.22)	(.25)
Observations	228	228	228	228	228	228
Adjusted R^2	.92	.88	.89	.83	.80	.24
5^{th}- 1^{st}	**.70*** (.24) Annualized: 8.4%**					
Panel C: Factor model without value factor						
Intercept	−.06	.04	.01	.44**	.47**	.53**
	(.09)	(.12)	(.12)	(.17)	(.20)	(.23)
Observations	228	228	228	228	228	228
Adjusted R^2	.93	.90	.89	.84	.82	.14
5^{th}- 1^{st}	**.53** (.22) Annualized: 6.4%**					
Panel D: Factor model with momentum factor						
Intercept	−.02	.09	.02	.58***	.56***	.58***
	(.09)	(.12)	(.13)	(.16)	(.18)	(.21)
Observations	228	228	228	228	228	228
Adjusted R^2	.93	.90	.89	.85	.84	.23
5^{th}- 1^{st}	**.58*** (.20) Annualized: 7.0%**					
Panel E: Two year lag structure across all industries						
Intercept	−.07	.02	.001	.48***	.22	.29*
	(.09)	(.12)	(.11)	(.13)	(.15)	(.18)
Observations	228	228	228	228	228	228
Adjusted R^2	.93	.89	.90	.90	.87	.15
5^{th}- 1^{st}	**.29* (.18) Annualized: 3.5%**					
Panel F: Three year lag structure across all industries						
Intercept	−.02	.01	−.07	.25*	.41**	.43**
	(.10)	(.15)	(.14)	(.14)	(.17)	(.19)
Observations	216	216	216	216	216	216
Adjusted R^2	.94	.91	.90	.89	.85	.06
5^{th}- 1^{st}	**.43** (.20) Annualized: 5.1%**					

This table reports monthly abnormal returns of value-weighted portfolios based on *PEFV*PE/TA* for several robustness analyses. Panel A shows results for assigning firms to portfolios per industry. Panel B reports results of reducing the sample to firms from countries with highly liquid traded currencies (i.e., EUR and GBP). Panel C excludes the value factor from the factor model. Panel D supplements the factor model with the momentum factor. Panel E (Panel F) shows results for applying the same lag structure of two (three) years to firms from all industries. Coefficients on the risk factors are not reported. Robust standard errors are shown in parentheses. *, **, *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 9: Long-term portfolio returns

	Year 1				
	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}
Intercept	−.06	.06	.03	.55***	.59***
	(.09)	(.12)	(.12)	(.16)	(.18)
Observations	228	228	228	228	228
Adjusted R^2	.93	.90	.89	.85	.84
5^{th}- 1^{st}	**.65*** (.21) Annualized: 7.8%**				
	Year 2				
	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}
Intercept	−.03	.04	.14	.55***	.40**
	(.11)	(.14)	(.14)	(.16)	(.16)
Observations	216	216	216	216	216
Adjusted R^2	.93	.88	.89	.83	.87
5^{th}- 1^{st}	**.43** (.19) Annualized: 5.1%**				
	Year 3				
	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}
Intercept	−.0004	.14	−.04	.37**	.25
	(.10)	(.14)	(.12)	(.17)	(.16)
Observations	204	204	204	204	204
Adjusted R^2	.93	.89	.92	.89	.85
5^{th}- 1^{st}	**.25 (.19) Annualized: 3.1%**				

This table reports monthly abnormal returns of value-weighted portfolios based on *PEFV*PE/TA* up to the third year after portfolio formation following the same procedure as in Table 7. Coefficients on the risk factors are not reported. Robust standard errors are shown in parentheses. *, **, *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 10: Cross-sectional future monthly returns

	Dependent variable:					
	$(R_{i,\tau} - R_{f,\tau})_{t+1}$				$(R_{i,\tau} - R_{Ind,\tau})_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
PEFV-Quintile$_{i,t}$	**.085*****		**.081*****		**.080*****	
	(.026)		**(.030)**		**(.030)**	
PEFV*PE/TA-Quintile$_{i,t}$		**.210*****		**.168*****		**.167*****
		(.029)		**(.036)**		**(.036)**
$Momentum_{-1,0}$	−.032***	−.033***	−.034***	−.034***	−.036***	−.037***
	(.007)	(.007)	(.008)	(.008)	(.008)	(.008)
$Momentum_{-12,-1}$	.007*	.006	.004	.004	.004	.003
	(.004)	(.004)	(.005)	(.005)	(.005)	(.005)
$Accruals_{i,t}$	.015	−.008	−.200	−.200	−.186	−.199
	(.145)	(.144)	(.181)	(.182)	(.182)	(.182)
$AssetGrowth_{i,t}$	−.157	−.153	−.423*	−.409*	−.410*	−.391*
	(.181)	(.182)	(.216)	(.216)	(.210)	(.209)
$log(BE/ME)_{i,t}$	.380***	.460***	.604***	.640***	.607***	.645***
	(.075)	(.075)	(.092)	(.093)	(.087)	(.089)
$log(ME)_{i,t}$	.287***	.329***	.309***	.332***	.306***	.329***
	(.036)	(.038)	(.041)	(.042)	(.041)	(.042)
$SGA/TA_{i,t}$			.568*	.354	.519*	.299
			(.304)	(.309)	(.309)	(.315)
$RND/TA_{i,t}$			5.272***	4.641***	5.195***	4.676***
			(1.561)	(1.551)	(1.441)	(1.458)
$EBITDA/TA_{i,t}$			2.424***	2.420***	2.395***	2.411***
			(.685)	(.689)	(.663)	(.669)
Intercept	−1.241***	−1.844***	−1.608***	−1.940***	−2.325***	−2.667***
	(.437)	(.430)	(.501)	(.498)	(.446)	(.454)
Observations	109,908	109,908	72,824	72,824	72,824	72,824
R^2	.290	.291	.310	.311	.093	.094

This table reports results from average Fama and MacBeth (1973) regression coefficients for monthly returns regressed on various firm and return characteristics. The monthly returns are from July *t+1* to June *t+2*. *, **, *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 11: Portfolios for alternative methodology to extract investment portion of PE

	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}
Panel A: Portfolios around *PEInvest*					
Intercept	.01	.18*	.05	.12	.49***
	(.11)	(.10)	(.10)	(.11)	(.15)
Observations	258	258	258	258	258
Adjusted R^2	.93	.94	.93	.91	.89
5^{th}- 1^{st}	**.48*** (.18) Annualized: 5.8%**				
Panel B: Portfolio assignment per FF12-industry					
Intercept	−.03	.12	.04	.40***	.22*
	(.11)	(.09)	(.09)	(.11)	(.13)
Observations	258	258	258	258	258
Adjusted R^2	.94	.94	.95	.92	.89
5^{th}- 1^{st}	**.25 (.17) Annualized: 3.0%**				

This table reports monthly abnormal returns of value-weighted portfolios based on *PEInvest*. Coefficients on the risk factors are not reported. Robust standard errors are shown in parentheses. *, **, *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.