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The Stock Market Valuation of Human Capital Creation

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Abstract

We develop measures of firm-level human capital creation from publicly disclosed personnel expenses (PE) and examine the stock market valuation of these characteristics. Separately measuring human capital creation *efficacy* and *opportunity*, we first show that efficacy is positively associated with characteristics of human-capital-intensive firms and employee productivity growth. Next, we find that efficacy has a positive pricing coefficient, implying that the market recognizes some of its variation. In our main analysis, long-short portfolios based on the human capital creation efficacy (opportunity) produce annualized abnormal returns of 4.0 to 5.4% (6.0 to 7.5%). Portfolios formed on the combination of efficacy and opportunities produce the strongest abnormal returns of 6.3 to 9.3% in annualized terms. Our results provide evidence of the importance to valuation of accurate human capital measurement.

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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 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 the component of PE that is most likely to reflect the efficacy of prior investments in human capital. Our main analysis examines whether this component of PE, as well as the total PE line item, predict future performance, and whether market participants recognize and appropriately value the different components.

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 1991 to 2018, capital expenditures as a percentage of total sales remained relatively flat at about 10%. On the other hand, PE almost doubled during

[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, costs for employee training and development, perquisites like catering and work wear, and post-termination benefits.

that time. By 2018, *PE* consumed approximately half 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, 2019b).

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 (Rouen, 2019a; Schiemann and Guenther, 2013). 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).

This paper takes steps to further the nascent literature on the relations among employee expenditures, human capital creation, and firm performance. Adapting a methodology to extract from an expenditure the intangible assets created by that expenditure (e.g., Banker et al., 2019; Chen et al., 2012; Huson et al., 2012; Lev and Sougiannis, 1996), we begin by calculating from *PE* the variation in firms' *efficacy* in creating human capital by identifying the relation between prior period *PE* and current firm performance, using a methodology similar to Banker et al. (2019). Specifically, for a large sample of firms across 30 European countries, 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.[3] In some industries, as many as three or four 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, or *PEFV*. We view total *PE* scaled by total assets as a proxy for a firm's *opportunity* to create human capital, while *PEFV* represents a proxy for the *efficacy* of that investment.

[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.

We begin our empirical analysis by 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* have fewer employees, higher market-to-book ratios, fewer tangible assets, higher sales growth, and more training for employees. That faster growing and less capital-intensive firms have higher *PEFV* provides us with confidence in this measure as an effective proxy for investments in human capital. Adding to this confidence, *PEFV* is positively associated with various measures of future employee productivity, providing evidence that investments in human capital lead to future productivity gains.

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 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 creating efficacy 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.

Our main analysis examines whether the market fully recognizes the future value of the intangible asset included in *PE*. To do so, we build portfolios around three different aspects of the future intangible asset value of *PE*. First, we sort firms into portfolios on the efficacy of the firm to generate future values from *PE* (i.e., *PEFV*). Second, we sort firms into portfolios based on current *PE*, scaled by total assets (PE/TA) as a proxy for firms' *opportunities* to develop human capital. Third, we sort firms into portfolios based on the interaction of efficacy and opportunity (i.e., *PEFV*PE/TA*).

Our portfolio analyses produce statistically and economically meaningful results. A long-short investment strategy based on the level of *PEFV* returns annualized abnormal returns of between 4.0% and 5.4% in the following year, while a strategy that divides firms into portfolios based on *PE/TA* results in abnormal annualized returns of between 6.0%

and 7.5% in the subsequent year. Importantly, the largest returns to this trading strategy arise from portfolios based on the interaction of $PEFV$ and PE/TA. The annualized long-short strategy based on the interaction of these measures leads to an abnormal annualized return of between 6.3% and 9.3% in the subsequent year, suggesting that the market fails to fully impound both the opportunity and efficacy of human capital development embedded in PE. These economically significant returns are robust to equal- or value-weighting the portfolios. They are also robust to using various factor models and excluding companies trading in countries with illiquid currencies. Our results also remain unchanged when conducting Fama-MacBeth cross-sectional regressions (Fama and MacBeth, 1973).

While sorting on the combination of human capital creation opportunity and efficacy results in the largest abnormal returns, we also observe a notable persistence in abnormal returns when sorting based on opportunity for the two and three years after the expense is recognized. Therefore, in our last series of tests, we examine the extent to which the abnormal returns around PE/TA can be assigned to markets mispricing the cross-sectional variation in the future intangible asset value of PE, and the extent to which markets require a risk premium for firms with high PE/TA. We find strong support for mispricing but also find some support for the risk factor explanation. Taken together, our results suggest that firms' personnel expenditures reflect not just the cost of labor in the current period but also the investment in human capital contained within that cost, and that market participants fail to fully understand the opportunity and efficacy of human capital development embedded in the disclosure of the expense.

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.

[4]Papers that examine labor expenses' relation to firm market value are Schiemann and Guenther (2013) and Ballester et al. (2002), which we discuss in section 2.

Second, 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.

Third, we contribute to two ongoing regulatory debates. 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). In this respect, our results may also be informative for the U.S. Securities and Exchange Commission, which recently 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 remainder of this paper is organized as follows. Section 2 develops the hypotheses. Section 3 describes the data used and the research design. Section 4 reports descriptive statistics, and section 5 describes the main empirical results and robustness analysis. Section 6 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 Hypothesis formulation

Recent research investigates whether investors understand firms' ability to create intangible assets from input resource expenditures. Banker et al. (2019) finds that investors recognize some of the future value of SG&A. The paper also finds subsequent abnormal returns based on the future value of SG&A that likely stem from market mispricing.[6] Eberhart et al. (2004) documents an initial under-reaction and subsequent positive abnormal returns when firms increase their R&D expenditure. Lev and Sougiannis (1996) adjusts firms' reported earnings and book values for the future value of R&D. The paper finds that such adjustments are relevant to investors and that there is a significant intertemporal association between the ability to create an intangible asset from R&D and subsequent stock returns.

Building on this literature, we examine personnel expenditures as they relate to the firm's efficacy in creating human capital as an intangible asset. Schiemann and Guenther (2013) analyzes *PE* in a U.K. sample and finds that the total personnel expense incrementally predicts subsequent earnings and returns. Ballester et al. (2002) examines a subsample of U.S. firms that voluntary disclose labor expenses and finds that the proportion of these costs that represents an investment in human capital is substantial. Moreover, the paper finds that the human capital asset accounts for about 16% of the difference in the market and book value of the firm.

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*.

We begin by examining the contemporaneous relation between stock price and $PEFV$,

[6] Enache and Srivastava (2017) offers another recent approach to measure the intangible investment character of SG&A. That approach focuses on separating the portion of the expenditure that supports current operations from the portion that is associated with future earnings. The approach by Banker et al. (2019), which we mainly follow, focuses on differentiating between firms that are better or worse at generating intangible value from input resources.

our proxy for the efficacy of the human capital investment. While a portion of PE is consumed contemporaneously to ensure the continuation of current operations of a firm, PE also contains personnel investments to attract and retain talent, and train workers to improve operations in the future (Flamholtz, 1971). Firm characteristics should dictate the optimal distribution of PE between current expenses and effective investment in the future (i.e., $PEFV$), and we expect significant variation in this distribution (Schiemann and Guenther, 2013; Ballester et al., 2002). Given the growing importance of human capital to firms' operations, markets should realize at least some of the human capital quality when it is created (Edmans, 2011; Pantzalis and Park, 2009). Thus, we state a directed hypothesis as follows:

H1: The contemporaneous pricing coefficient on $PEFV$ is positive.

Given the lack of detailed disclosure on personnel expenditures and human capital investment, it is unclear whether the stock market fully recognizes firms' human capital creating ability when this information is indirectly disclosed. Numerous prior studies show that markets do not fully incorporate intangible asset values when they are created (e.g., Banker et al., 2019; Chan et al., 1990, 2001; Eberhart et al., 2004; Edmans, 2011; Lev and Sougiannis, 1996). To shed light on the effective pricing of human capital, we next explore the relation between various measures of future values implicit in personnel expenditures and future stock returns.

One way in which this paper advances the literature is by separately examining the opportunity to develop human capital (PE) from the efficacy of that investment ($PEFV$), measured at the time when the investment is consumed. Given the lack of information about this investment, it is plausible that stock markets misprice firms that generate high future values from PE. Moreover, such firms could have more risk and uncertainty (Ballester et al., 2002). Because firms do not own their employees, human capital is reduced when employees leave the firm (Lev and Schwartz, 1971). Thus, contingent with both the mispricing and the risk factor explanation, we hypothesize that:

H2a: $PEFV$ is positively associated with future abnormal returns.

We next examine the relation between the current level of PE and future returns. PE, in part, represents a firm's opportunities to build human capital for future gains. While PE is expensed as incurred, a component of the expenditure can be thought of as similar to buying a machine that will continue to produce value during its useful life. Therefore, firms that invest heavily in building human capital understate their earnings (Lev, 2019). If the market fixates on reported earnings, these firms will be undervalued in the current period and generate abnormal returns in subsequent periods (Sloan, 1996).

At the same time, firms with high PE may be riskier on average. Opportunities to grow the firm's human capital do not necessarily reflect the efficacy of those investments, creating greater uncertainty about the firm's expected future income (Lev and Schwartz, 1971). PE may also be difficult or costly to adjust in the short run, leading to high labor leverage, which results in firms' operating profits being more sensitive to shocks and which is positively associated with firms' equity risk (Rosett, 2003; Donangelo et al., 2019). This could lead markets to demand a risk premium (Donangelo et al., 2019). Thus, there should be a positive relation between subsequent abnormal returns and the total level of PE.

H2b: Total PE is positively associated with future abnormal returns.

Firm performance can be impacted by both the opportunity to create human capital and the efficacy of management in creating that human capital. An incrementally higher total PE provides greater benefit for a firm that is also more effective at investing that PE. Consequentially, the correct pricing of the combination of opportunity and efficacy may be a significant challenge to investors. In addition, firms with greater opportunity and greater efficacy are particularly risky, potentially leading investors to demand a corresponding risk premium.

H2c: The interaction of *PEFV* with total *PE* is positively associated with future abnormal returns.

3 Data, variable creation, and research design

3.1 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 11,866 non-financial and non-utilities firms (e.g., He and Narayanamoorthy, 2019) that were active at some point in time during the period 1990 to 2018. For those firms, we obtain Thomson Reuters Datastream data for 130,793 firm-years from 1991 to 2018, which begins one year later since we use average total assets (*TA*) to deflate the financial statement variables. 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 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 76,674 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 1995 to 2018. Removing FF12-industry-years with less than

[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.

15 firms gives the sample of 40,474 firm-years used to obtain the optimal lag structure per FF12-industry. Of that sample, 25,976 firm-years have sufficient lagged data to allow the firm-year-specific calculation of the human capital creation efficacy (i.e., the personnel expenditure future value, $PEFV$). The earliest year where such a calculation is possible is 1997. Our final sample contains 13,116 positive $PEFV$ firm-years beginning in 1998.

Panel B of Table 1 shows the distribution of firm-years among countries and FF12-industries for the 25,976 $PEFV$ 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.

3.2 Measurement of personnel expenditure future value

We begin our analysis of the human capital creation efficacy implicit in PE by estimating the long-term effect of contemporaneous PE on future 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:

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

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 FF12-industry with different numbers of lags (different n).[8] $OI/TA_{i,t}$ 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 the following instrumental variables

[8]Banker et al. (2019) considers models ranging from zero to seven years, Huson et al. (2012) considers 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) finds 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.

approach for the deflated PE of year $t-k$:

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).[9] 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.[10] 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 incomes (Ciftci and Cready, 2011) and also include year indicators (η_t). For each FF12-industry, we determine the lag structure with all positive and statistically significant (at the 10% level) coefficients and the most explanatory power.[11]

Second, we fix the optimal lag structure from the first step for all firms of a given industry. We next rerun equation (1) (excluding the proxy for firm size) at the firm-year level. 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.[12] We use rolling windows of historical years in the firm-specific regressions using

[9]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.

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

[11]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.

[12]For instance, for a firm with full data coverage from 1991 to 2018, 1995 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

the number of lags determined at the industry level in the first stage. $PEFV_{i,t}$ 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 creating efficacy.[13] It reflects the total effect of a currency unit of spending of current *PE* on future *OI*.

3.3 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) for *each* industry. 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 0.420 and 0.491. It thus appears that a substantial portion of *PE* is a value-creating investment on 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 four. Past *PE* has no impact on current *OI* in the Chemicals & Allied Products industry. The lag structure persists into three or four earlier years in industries like Consumer Durables and Manufacturing. It appears meaningful that firms' human capital creating efficacy is particularly important in consumer-oriented industries where firms can add relatively high value to the products and services they offer (Banker et al., 2011). Overall, the results support the notion that the magnitude of the future values generated by *PE* varies considerably across industries.

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.

[13] 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.

4 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 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 \$2,472 million (\$176 million) and the mean (median) *PE* value is \$358 million (\$36 million). The mean (median) *PE* scaled by average *TA* (*PE/TA*) amounts to 0.29 (0.24). These figures are in the range of Banker et al. (2019)'s analysis of SG&A. Panel B describes the sample where $PEFV$ can be calculated (25,976 observations). 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. Panel C shows descriptive statistics for the final sample of positive $PEFV$ firm-years. $PEFV_{i,t}$ is a highly right-skewed variable. We therefore winsorize it at the 95% level. The resulting mean value is 2.17, and the median is 1.31. Panel C also describes the variables used in the contemporaneous price analyses. All variables are defined in Appendix A.[14]

4.1 *PEFV* and firm characteristics

To assess the plausibility of $PEFV$ as a proxy for human capital creation efficacy, 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 $PEFV$. The $PEFV$ deciles are the dependent variable in columns (1) to (8). 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. The change in sales as a proxy for firm growth

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

loads significantly positively. The former year's 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 (7), our inferences remain unchanged, with the exception of the coefficient on average pay measure, which becomes negative and marginally significant. Column (8) reports the relation between the average training days per employee in the prior year and $PEFV$ for the subsample of firms that report this information. Consistent with $PEFV$ being associated with human capital creation, the coefficient on *TrainingDays* is positive and significant.

In columns (9) to (11) we assess whether $PEFV$ is associated with future employee productivity. The ultimate goal of human capital investments is increased profitability, but employee productivity is more likely to be a first-order outcome measure of this investment, given that investments in employees are made to improve their direct output (Kotsantonis and Serafeim, 2020). Similar to Kotsantonis and Serafeim (2020), we measure employee productivity along three different income statement dimensions: *OI*, *OI* before depreciation, amortization and *PE*, and total sales, all scaled by total employees. In these regressions, we include current productivity and firm and year fixed effects, meaning that the coefficient on $PEFV$ can be interpreted as the relation between $PEFV$ and the change in productivity. In all specifications, the coefficient on $PEFV$ is positive and significant, suggesting that greater human capital investment efficacy is associated with future employee productivity. Overall, these results lend credence to the claim that $PEFV$ is an intuitive proxy for human capital creation efficacy.

5 Stock market valuation of human capital creation

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

5.1 Contemporaneous stock prices and *PEFV*

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

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

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. Our first hypothesis, that the future value of human capital creation efficacy will have a positive relation with contemporaneous price, predicts 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, γ will be negative.

Table 5 shows the regression results of testing the first hypothesis. 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 high $PEFV$ (i.e., high human capital creating efficacy) is reflected in contemporaneous prices.

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 $PEFV$. Columns (1) and (2) show that reducing the sample to include only $PEFV$ values larger zero does not substantially affect the coefficients for $OIPS_{i,t}/P_{i,t-1}$ 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 positive pricing coefficient of $PEFV$ and switches the sign on the pricing coefficient of current PE. We show results of two alternative measures of the future value of PE in columns (8) and (9). We multiply $PEFV$ with current PE per share to obtain a combination of the future value creating efficacy with current PE measured in U.S. dollar in column (8). $PEFV * PEPS_{i,t}/P_{i,t-1}$ is significantly positively related with contemporaneous stock prices. The coefficient on current PE turns insignificant in this specification. In column (9), we consider the deciles measure of $PEFV$ that we use in Table 4 as an alternative, which also has a significantly positive pricing coefficient. In column (10), we present results for the sample of non-negative firm-years as in Banker et al. (2019). Finally, in column (11), we present results for a subsample where high values of $PEFV$ (above the upper 5% of the distribution) are treated as measurement errors and excluded from the analysis. The results presented in Table 5 provide strong support for our hypothesis that investors recognize some of the human capital creating efficacy contemporaneously.[15]

[15]While Banker et al. (2019) finds 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 $SGAFV$ regarding contemporaneous price changes and further stresses the importance of understanding human capital investment for valuation purposes.

5.2 Future portfolio returns

Model (3) is not suitable to test whether investors fully capture firms' human capital creation implicit in *PE*. We therefore turn to future portfolio return analyses around human capital creation in our next set of tests to test hypotheses 2. Our main results are based on the five-factor model (Fama and French, 2015) as follows.

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

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).[16] 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).[17]

The variable of interest in equation (4) is the intercept α which measures the abnormal return. Hypotheses 2a-2c predict that α will increase with portfolios built from higher quintiles. $R_{p,\tau}$ 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 a 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 association with the investment aggressiveness factor.

We form portfolios based on three different measures for the future intangible asset

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

[17] 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.

value of PE. First, we consider quintiles of our measure of human capital creation efficacy ($PEFV$). Second, as $PEFV$ is backward looking by construction and may be subject to estimation error, we consider a straightforward measure of human capital creation opportunities, i.e., firms' PE deflated by average TA (PE/TA). Third, we form portfolios based on the measure that interacts $PEFV$ with current PE ($PEFV * PE/TA$). This measure implicitly combines the historically estimated intangible value generating efficacy with the current opportunity set. 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 (13,116 observations) to create these portfolios. The human capital creation opportunities measure (i.e., PE/TA) does not require the same condition, so we form portfolios on PE/TA using the full samples of 25,967 observations for these portfolios.[18]

Table 6 shows the results for the main quintile portfolio analyses in the 12 months after portfolio formation. Portfolios in the tables are built based on $PEFV$, PE/TA, and $PEFV * PE/TA$ quintiles. The first row reports raw returns of the equal-weighted portfolios in excess of the risk-free rate. The annualized difference in the raw returns between the highest and the lowest quintile is 3.0% for $PEFV$, 4.2% for PE/TA, and 5.1% for $PEFV * PE/TA$, which suggests that firms with higher human capital creation among all dimensions have higher 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 returns are 4.0% for $PEFV$ and 6.4% for both PE/TA and $PEFV * PE/TA$. 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.[19] The abnormal returns for the value-weighted portfolios are generally more extreme, with annualized long-short

[18] We obtain qualitatively similar results when we do the PE/TA portfolio analyses using the initial sample of 76,674 firm-years, providing confidence that sample selection decisions are not driving our results.

[19] Interestingly, the exposure to the value factor for the fifth quintiles is close to zero or even significantly negative which is in line with portfolio results for firms with high employee satisfaction reported by Edmans (2011).

returns of 5.4% for $PEFV$ 7.5% for PE/TA, and 7.8% for $PEFV * PE/TA$. 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 human capital investment opportunity and efficacy.

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. However, this model does not control for momentum in stock returns. We therefore corroborate our findings with a six factor model that adds momentum (MOM_τ) to the main model. Panel A of Table 7 shows the results for the equal- and value-weighted abnormal returns after controlling for the six factors. As before, the long-short returns are significantly positive and the annualized figures are similar.

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 rather illiquid, which may lead to strong fluctuations of the exchange rate between the respective currency and the dollar. Such strong fluctuations may have an impact on the return measurement, which may impact 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.[20] Panel B of Table 7 shows that we continue to find significant abnormal returns. For this subsample, the annualized abnormal value-weighted long-short returns for the combination of efficacy and opportunities increases to 9.3%.

5.3 Additional analyses

5.3.1 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. Table 8 shows equal-weighted

[20] 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.

abnormal returns for the three aspects of human capital creation using our main risk factor model. In Panel A, we observe that the sort on $PEFV$ still produces abnormal long-short returns in the second year after portfolio formation and turns insignificant in the third year. $PEFV$ estimates firms' (historic) efficacy in the creation of human capital. It appears meaningful that sorting on this variation leads to abnormal returns in the earlier years after a high efficacy manifests rather than the later years. Panel B shows strong persistence in the abnormal returns conditioning on the opportunities to invest in human capital as the abnormal annualized long-short return is even higher in the second and third year after portfolio formation. Much of this persistence is likely due to little turnover in the PE/TA portfolios as PE/TA is highly auto-correlated at the firm level.[21] Consequently, Panel C also shows persistence in abnormal returns for the combined measure of efficacy and opportunities that may be mainly driven by the opportunities characteristic.

5.3.2 Cross-sectional future returns

We report abnormal returns in line with standard approaches in the accounting and finance literature in our main tests. 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 9 reports that monthly returns for the one-year-ahead period, using Fama-Macbeth regressions, are 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). Appendix C shows that these associations persist into the second and third years after the future value measurement, in line with our long-term portfolio returns.

[21] The firm-level Pearson correlation between quintiles of PE/TA and lagged PE/TA is 0.94. This persistence raises the question of whether the observed abnormal returns can be fully assigned to mispricing or whether there is compensation for a systematic risk factor involved. We further analyze the differentiation between the two explanations below.

5.3.3 Risk versus mispricing

To further investigate the notable persistence in abnormal returns based on our measure for human capital creation opportunities (PE/TA), we assess whether the proposed subsequent abnormal returns are more likely due to risk or mispricing. We follow the five step factor mimicking methodology used by Banker et al. (2019), similar to Hirshleifer et al. (2012). We then perform a formal test designed to differentiate between the two explanations. This process is described in detail in Appendix D.

Panel A of Table 10 describes the calculated risk factor of PE/TA. The mean (median) return on $PE/TAfactor_\tau$ is 0.39 (0.43) per month from July 1998 to June 2019. $PE/TAfactor_\tau$ appears to be a meaningful candidate for a risk factor with a mean monthly return higher than those of the size, the value, the profitability robustness, and the investment aggressiveness factors, and lower than the market factor over the same period.

Panel B of Table 10 shows the results of the corresponding average monthly Fama and MacBeth (1973) regression coefficients. Column (1) reports results for equal-weighted returns, and column (2) reports results for value-weighted returns. The coefficients for $PE/TA_{p,t}$ are significantly positive in both specifications. This indicates that the opportunities to build human capital (PE/TA) are mispriced by the market to a significant extent. The coefficient on the PE/TA factor loading is also significantly positive, which indicates that PE/TA also has characteristics of a systematic risk factor.

6 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 training, and with future employee productivity, 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 three aspects of the future intangible asset value of *PE*: the efficacy in developing human capital, the opportunity to make that investment, and the interaction of the two. Further tests provide strong evidence that these abnormal returns are due to mispricing but also show support for compensation for risk. The evidence supports the notion that markets fail to fully account for the intangible asset value generated by *PE*.

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 promising 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
$PEFV*PE_{i,t}$	$PEFV_{i,t}$ multiplied with $PE_{i,t}$ (measured in US$)
$PEFV*PE/TA_{i,t}$	$PEFV_{i,t}$ 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$)
$PEFV*PEPS_{i,t}$	$PEFV*PE_{i,t}$ divided by shares outstanding (in US$)
$SGAPS_{i,t}$	SG&A expenses (WC01101) per share (in US$)
$RNDPS_{i,t}$	R&D expenses (WC01201, set to zero if missing) 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$)
$MTB_{i,t}$	End of year market-to-book ratio (MTBV)
$Tangibility_{i,t}$	End of year property, plant & equipment (WC02501) scaled by total assets
$SalesGrowth_{i,t}$	Change in total sales (WC01001) from $t-1$ to t scaled by $t-1$
$MeanPay_{i,t}$	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)
$OIPS_{i,t}/P_{i,t-1}$	0.295**	0.298**	0.302***	0.305***
	(0.120)	(0.119)	(0.111)	(0.110)
$PEPS_{i,t}/P_{i,t-1}$	−0.138	−0.147	−0.250**	−0.257**
	(0.126)	(0.124)	(0.113)	(0.112)
$\boldsymbol{PEFV_{i,t}/P_{i,t-1}}$		**0.039****		**0.037****
		(0.016)		**(0.016)**
$EPS_{i,t}/P_{i,t-1}$	1.706***	1.706***	1.840***	1.839***
	(0.229)	(0.229)	(0.202)	(0.202)
$SGAPS_{i,t}/P_{i,t-1}$			0.137***	0.134***
			(0.042)	(0.041)
$RNDPS_{i,t}/P_{i,t-1}$			1.758***	1.744***
			(0.437)	(0.431)
$\boldsymbol{SGAFV_{i,t}/P_{i,t-1}}$	**0.046***	**-0.009**	**0.028**	**-0.023**
	(0.025)	**(0.022)**	**(0.023)**	**(0.021)**
Intercept	0.914***	0.921***	0.876***	0.883***
	(0.016)	(0.017)	(0.018)	(0.017)
FF12 dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Observations	3,262	3,262	3,262	3,262
Adjusted R^2	0.356	0.359	0.370	0.373

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 25,976 *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.

Appendix C - Long-term cross-sectional returns

	Dependent variable:			
	$(R_{i,\tau} - R_{f,\tau})_{t+2}$	$(R_{i,\tau} - R_{Ind,\tau})_{t+2}$	$(R_{i,\tau} - R_{f,\tau})_{t+3}$	$(R_{i,\tau} - R_{Ind,\tau})_{t+3}$
	(1)	(2)	(3)	(4)
PEFV-Quintile$_{i,t}$	**.092****	**.101*****	**.080***	**.096****
	(.037)	**(.038)**	**(.041)**	**(.040)**
PE/TA-Quintile$_{i,t}$	**.222*****	**.261*****	**.206*****	**.213*****
	(.049)	**(.051)**	**(.064)**	**(.057)**
$Momentum_{-1,0}$	$-.027^{***}$	$-.030^{***}$	$-.032^{***}$	$-.035^{***}$
	(.008)	(.008)	(.009)	(.008)
$Momentum_{-12,-1}$	.005	.004	.006	.004
	(.004)	(.004)	(.004)	(.004)
$Accruals_{i,t}$	.013	.173	$-.611^{**}$	$-.526^{**}$
	(.227)	(.268)	(.257)	(.242)
$AssetGrowth_{i,t}$	.127	.097	$-.248$	$-.222$
	(.199)	(.198)	(.201)	(.197)
$log(BE/ME)_{i,t}$	$.463^{***}$	$.438^{***}$	$.483^{***}$	$.473^{***}$
	(.104)	(.102)	(.094)	(.091)
$log(ME)_{i,t}$	$.317^{***}$	$.319^{***}$	$.332^{***}$	$.336^{***}$
	(.045)	(.044)	(.050)	(.051)
$SGA/TA_{i,t}$	.081	.087	$.838^{*}$	$.834^{*}$
	(.353)	(.359)	(.435)	(.428)
$RND/TA_{i,t}$	4.260^{**}	4.552^{***}	2.483	2.464^{*}
	(1.713)	(1.509)	(1.568)	(1.436)
$EBITDA/TA_{i,t}$	$-.116$	$-.300$	.332	.040
	(.708)	(.721)	(.742)	(.701)
Intercept	-2.375^{***}	-3.117^{***}	-2.176^{***}	-3.080^{***}
	(.507)	(.446)	(.543)	(.476)
Observations	78,889	78,889	71,779	71,779
R^2	.273	.084	.274	.089

This table reports results from average Fama and MacBeth (1973) regression coefficients for monthly returns regressed on various firm and return characteristics where the monthly returns are from July *t+2* to June *t+3* in columns (1) and (2) and from July *t+3* to June *t+4* in columns (3) and (4). *, **, *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Appendix D - Factor mimicking methodology

In the first step, we construct monthly factor returns for PE/TA. We assign stocks into two size groups (small and big) based on firms' market capitalization at the end of June of year $t+1$. We also assign stocks independently into the low 30%, medium 40%, and high 30% groups regarding PE/TA[22], where PE/TA is measured at fiscal year end of year t. The intersections of the size groups and the PE/TA groups are used to form six portfolios. The difference between the equal-weighted average of the returns on the two high PE related portfolios (small-high, big-high) and the two low portfolios (small-low, big-low) is $PE/TAfactor_{\tau}$. We thereby value-weight the monthly returns measured from July of year $t+1$ until June of year $t+2$ on the

[22]As before, we focus on the firm-years of the $PEFV$ calculation sample.

double-sorted portfolios (Banker et al., 2019; Hirshleifer et al., 2012).

In the second step, we obtain firm-year-specific factor loadings for $PE/TAfactor_\tau$ in the preformation period. We add the factor to the five-factor model (Fama and French, 2015) used before and estimate factor loadings over the 60 month rolling window (24 months minimum) prior to end of June of year $t+1$ portfolio formation, applying model

$$\begin{aligned} R_{i,\tau} - R_{f,\tau} = \alpha + \beta_{PE/TAfactor} PE/TAfactor_\tau + \beta_{market}(R_{m,\tau} - R_{f,\tau}) + \beta_{size} \\ SMB_\tau + \beta_{value} HML_\tau + \beta_{profit} RMW_\tau + \beta_{invest} CMA_\tau + \varepsilon_\tau. \end{aligned} \tag{5}$$

$R_{i,\tau} - R_{f,\tau}$ is firm-level return in excess of the risk-free rate in month τ. The coefficient on $PE/TAfactor_\tau$ is the firm-year-specific preformation factor loading as of June in year $t+1$. The five Fama French factors are the same as in the portfolio return analyses.

In the third step, we form triple-sorted portfolios. Similar to the first step, we now assign stocks independently into three groups each according to size and PE/TA with breakpoints on the 33^{rd} and 67^{th} percentile. We further divide the stocks in the resulting nine double-sorted portfolios into three groups[23] based on the respective preformation factor loading obtained in the second step. We arrive at 27 portfolios.

The fourth and the fifth step correspond with the two steps of the Fama and MacBeth (1973) methodology to determine betas and risk premia for risk factor candidates. The fourth step comprises estimating portfolio-level factor loadings. For each of the 27 portfolios, we regress equal-weighted (Banker et al., 2019)[24] monthly returns in excess of the risk-free rate on the same six factors from equation (5). We estimate the portfolio-year-specific factor loadings as the coefficients of the 60 month rolling window (24 months minimum) prior to portfolio formation. Thus, the coefficients $\beta_{PE/TAfactor_{p,t}}$, $\beta_{market_{p,t}}$, $\beta_{size_{p,t}}$, $\beta_{value_{p,t}}$, $\beta_{profit_{p,t}}$, and $\beta_{invest_{p,t}}$ are the June $t+1$ portfolio-level factor loadings.

In the fifth step, we regress monthly portfolio-level returns on the factor loadings estimated in the fourth step as in the following model:

$$\begin{aligned} R_{p,\tau} = \alpha + \gamma_{variable} PE/TA_{p,t} + \gamma_{factor}\beta_{PE/TAfactor_{p,t}} + \gamma_{market}\beta_{market_{p,t}} + \\ \gamma_{size}\beta_{size_{p,t}} + \gamma_{value}\beta_{value_{p,t}} + \gamma_{profit}\beta_{profit_{p,t}} + \gamma_{invest}\beta_{invest_{p,t}} + \varepsilon_{p,\tau}. \end{aligned} \tag{6}$$

The left-hand side of equation (6) is equal-weighted monthly portfolio returns from July of year $t+1$ to June of year $t+2$. $PE/TA_{p,t}$ represents the portfolio-level equal-weighted variable (Banker et al., 2019) as of fiscal year end t.[25] The other regressors are the six rolling window factors obtained in step four.

A positive coefficient on the PE/TA factor loading ($\gamma_{factor} > 0$) would imply that exposure to this factor predicts future returns. A positive coefficient on the actual level of $PE/TA_{p,t}$ ($\gamma_{variable} > 0$) would imply that the actual level predicts future returns, providing support for the mispricing explanation (Banker et al., 2019).

[23] This sort is again based on the 33^{rd} and 67^{th} percentile. Our approach follows Hirshleifer et al. (2012). We obtain similar results (not tabulated) when we do the preformation sort independent of the other two sorts (Banker et al., 2019).

[24] We present results for value-weighted returns (Hirshleifer et al., 2012) as an alternative.

[25] When presenting value-weighted returns as an alternative we also value-weight $PE/TA_{p,t}$.

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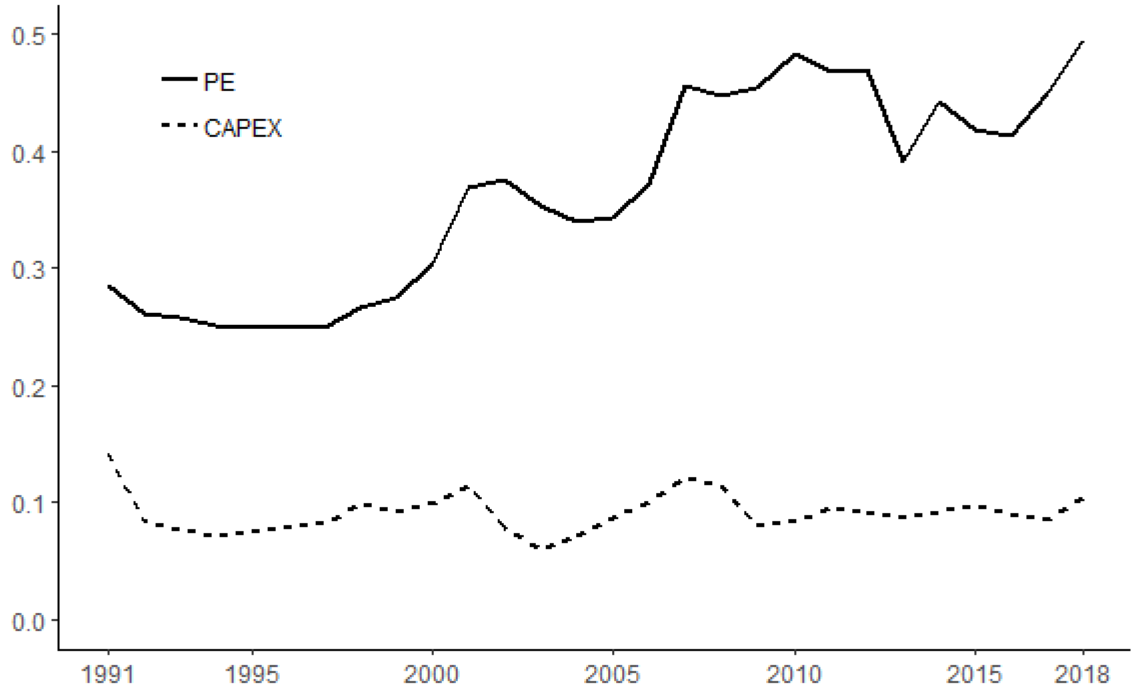
Figure 1: Development of personnel expenditure and capital expenditure over time



This figure plots the annual average personnel expenditure (solid line) and capital expenditure (dashed line) scaled by total sales over the sample period from 1991 to 2018.

Table 1: Sample selection and distribution

Panel A: Sample selection procedure

Selection step	Firms	Firm-years
Thomson Reuters Datastream annual data from 1991 to 2018 for non-financial firms from 30 countries	11,866	130,793
− firm-years with missing financial statement items, stock-related data and number of employees	(2,322)	(44,036)
− SIC-4-industry-years with less then five firms	(673)	(10,083)
Sample used to winsorize yearly and to estimate $(PE/TA_{predicted})_{i,t}$ with the instrumental variable approach	8,871	76,674
− firm-years with missing data in any of the preceding four years	(3,411)	(36,140)
− FF12-industry-years with less than 15 firms	(3)	(60)
Sample for estimation of optimal lag structure for each FF12-industry from 1995 to 2018	5,457	40,474
− firm-years with not sufficient data for firm-year-specific regressions	(1,827)	(14,498)
Sample for estimation of PEFV per firm-year from 1997 to 2018	5,457	25,976
− firm-years with negative PEFV	(608)	(11,690)
Sample with non-negative PEFV per firm-year (from 1997 to 2018)	3,022	14,286
− firms from industries with zero lags (zero PEFV)	(144)	(1,170)
Final sample with positive PEFV per firm-year from 1998 to 2018	2,878	13,116
− firm-years with missing forecast data	(667)	(3,161)
Subsample with forecast data availability (from 1998 to 2018)	2,211	9,955

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

Country	Firm-years	FF12-industry	Firm-years
Austria	397	(1) Consumer NonDurables	3,025
Belgium	570	(2) Consumer Durables	1,006
Denmark	825	(3) Manufacturing	3,473
Finland	901	(4) Oil, Gas, & Coal Extract. & Products	894
France	4,066	(5) Chemicals & Allied Products	1,170
Germany	3,464	(6) Business Equipment	5,261
Greece	157	(7) Telephone & Television Transmission	839
Hungary	86	(8) Utilities (excluded)	0
Ireland	415	(9) Wholesale, Retail, & Some Services	2,794
Italy	1,235	(10) Healthc., Medical Equipm., & Drugs	1,512
Luxembourg	79	(11) Finance (excluded)	0
The Netherlands	1,100	(12) Other	6,002
Poland	405	Total	25,976
Portugal	335		
Spain	857		
Sweden	1,319		
United Kingdom	7,578		
Switzerland	1,296		
Norway	676		
Others (less than 50: BG, CZ, EE, HR, LT, LV, MT, RO, SI, SK)	215		
Total	25,976		

Table 2: Lag structure regressions

Panel A: Cross-sectional regressions with different lag structures

	Dependent variable:			
	$OI/TA_{i,t}$			
	(1)	(2)	(3)	(4)
$(PE/TA_{predicted})_{i,t}$	0.609***	0.547***	0.510***	0.480***
	(0.036)	(0.037)	(0.037)	(0.037)
$(PE/TA_{predicted})_{i,t-1}$	0.462***	0.225***	0.205***	0.192***
	(0.036)	(0.044)	(0.044)	(0.044)
$(PE/TA_{predicted})_{i,t-2}$		0.313***	0.113***	0.101**
		(0.036)	(0.044)	(0.043)
$(PE/TA_{predicted})_{i,t-3}$			0.267***	0.090**
			(0.037)	(0.043)
$(PE/TA_{predicted})_{i,t-4}$				0.242***
				(0.035)
$log(\#E)_{i,t}$	0.023***	0.023***	0.023***	0.023***
	(0.001)	(0.001)	(0.001)	(0.001)
$Intercept$	−0.085***	−0.088***	−0.089***	−0.092***
	(0.010)	(0.010)	(0.010)	(0.010)
$\sum_{k=1}^{n} \beta_k/(1.1)^k$	0.420	0.463	0.480	0.491
Year dummies	Yes	Yes	Yes	Yes
FF12 dummies	Yes	Yes	Yes	Yes
Observations	40,474	40,474	40,474	40,474
AIC	−5895	−5988	−6057	−6115
SBC	−5585	−5669	−5729	−5780
Adjusted R^2	0.342	0.343	0.344	0.345

Panel B: Optimal lag structure per FF12-industry

FF12-industry	β_0	β_1	β_2	β_3	β_4	$\sum_{k=1}^{n} \beta_k/(1.1)^k$	$R^2_{adj.}$
(1) Consumer NonDurables	.478	.435				.396	.155
(2) Consumer Durables	.714	.346	.403	.514		1.03	.137
(3) Manufacturing	.318	.177	.142	.213	.304	.646	.207
(4) Oil, Gas, & Coal Extract. & Products	.564	.281				.255	.353
(5) Chemicals & Allied Products	.951					-	.154
(6) Business Equipment	.401	.641				.583	.178
(7) Telephone & Television Transmission	.141	.493				.448	.026
(8) Utilities (excluded)	-	-	-	-	-	-	-
(9) Wholesale, Retail, & Some Services	.685	.242	.251			.427	.309
(10) Healthc., Medical Equipm., & Drugs	.682	.779				.708	.344
(11) Finance (excluded)	-	-	-	-	-	-	-
(12) Other	.592	.202	.264			.402	.412

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 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 1991 to 2018

	N	Mean	STD	Min	25%	Median	75%	Max
$TA_{i,t}(\$m)$	76,674	2,472	12,674	1	45	176	744	397,812
$PE_{i,t}(\$m)$	76,674	358	1,418	0	9	36	149	40,950
$PE/TA_{i,t}$	76,674	0.29	0.24	0.002	0.13	0.24	0.38	1.62
$(PE/TA_{predicted})_{i,t}$	76,674	0.29	0.15	−0.20	0.19	0.27	0.35	1.38
$OI/TA_{i,t}$	76,674	0.36	0.29	−0.52	0.19	0.33	0.50	1.63

Panel B: Descriptive statistics of sample for estimation of *PEFV*

	N	Mean	STD	Min	25%	Median	75%	Max
$TA_{i,t}(\$m)$	25,976	4,770	19,368	1	99	355	1,777	397,812
$PE_{i,t}(\$m)$	25,976	635	1,946	0	24	85	348	40,950
$PE/TA_{i,t}$	25,976	0.30	0.24	0.004	0.14	0.24	0.38	1.62
$OI/TA_{i,t}$	25,976	0.39	0.27	−0.52	0.22	0.35	0.51	1.61
$P_{i,t}/P_{i,t-1}$	25,976	1.10	0.53	0.05	0.78	1.04	1.33	6.38
$OIPS_{i,t}/P_{i,t-1}$	25,976	0.59	0.56	0.01	0.20	0.40	0.79	2.16
$PEPS_{i,t}/P_{i,t-1}$	25,976	0.53	0.55	0.04	0.14	0.33	0.71	2.08

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

	N	Mean	STD	Min	25%	Median	75%	Max
$TA_{i,t}(\$m)$	13,116	5,001	20,873	1	100	366	1,821	396,812
$PE_{i,t}(\$m)$	13,116	633	1,876	0	25	88	347	35,650
$PEFV_{i,t}$	13,116	2.17	2.21	0.0001	0.50	1.31	3.08	7.05
$PEFV * PE_{i,t}(\$m)$	13,116	409	592	0.00	27	116	497	1,848
$PE/TA_{i,t}$	13,116	0.30	0.25	0.004	0.13	0.24	0.38	1.62
$PEFV * PE/TA_{i,t}$	13,116	0.73	1.29	0.00	0.08	0.27	0.80	23.30
$P_{i,t}/P_{i,t-1}$	13,116	1.09	0.51	0.06	0.79	1.03	1.30	6.63
$OIPS_{i,t}/P_{i,t-1}$	13,116	0.59	0.56	0.01	0.20	0.40	0.80	2.16
$PEPS_{i,t}/P_{i,t-1}$	13,116	0.54	0.55	0.04	0.15	0.33	0.73	2.08
$PEFV_{i,t}/P_{i,t-1}$	13,116	0.72	1.15	0.0000	0.03	0.15	0.76	3.60
$PEFV * PEPS_{i,t}/P_{i,t-1}$	13,116	0.99	1.25	0.00	0.11	0.40	1.31	3.92
$EPS_{i,t}/P_{i,t-1}$	9,955	0.07	0.06	−0.08	0.04	0.07	0.10	0.18
$SGAPS_{i,t}/P_{i,t-1}$	8,699	0.47	0.47	0.04	0.14	0.29	0.61	1.82
$RNDPS_{i,t}/P_{i,t-1}$	13,116	0.02	0.04	0.00	0.00	0.00	0.02	0.13

This table reports descriptive statistics for different samples. Panel A reports characteristics for the initial sample of firms from 1991 to 2018, Panel B reports descriptive statistics for the sample where the firm-year-specific $PEFV$ is calculated, and Panel C reports descriptive statistics for the final sample with positive $PEFV$.

Table 4: Firm characteristics and $PEFV$

	Dependent variable:										
	$PEFV - Decile_{i,t}$								$OI/\#E_{i,t+1}$	$OI^{BDNAPE}/\#E_{i,t+1}$	$Sales/\#E_{i,t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$PEFV - Decile_{i,t}$									5.254**	9.556***	14.207**
									(2.455)	(3.181)	(6.570)
$OI/\#E_{i,t}$									0.501***		
									(0.068)		
$OI^{BDNAPE}/\#E_{i,t}$										0.576***	
										(0.070)	
$Sales/\#E_{i,t}$											0.639***
											(0.038)
$log(\#E)_{i,t}$	−0.027***						−0.027***	−0.032***	5.640	2.818	−8.290
	(0.002)						(0.002)	(0.009)	(4.682)	(4.905)	(8.374)
$MTB_{i,t}$		0.007***					0.006***		1.588***	1.755***	1.386
		(0.002)					(0.001)		(0.482)	(0.585)	(1.159)
$Tangibility_{i,t}$			−0.130***				−0.081***		23.302	20.808	−22.023
			(0.023)				(0.024)		(25.432)	(25.287)	(57.622)
$PE/TA_{i,t}$				0.154***			0.145***		14.864	4.652	−19.579
				(0.017)			(0.017)		(10.601)	(13.865)	(17.758)
$SalesGrowth_{i,t}$					0.021**		0.013*				
					(0.008)		(0.008)				
$MeanPay_{i,t-1}$						0.0004***	−0.0002*				
						(0.0001)	(0.0001)				
$TrainingDays_{i,t-1}(\%)$								0.023*			
								(0.012)			
$Intercept$	0.778***	0.529***	0.599***	0.521***	0.557***	0.545***	0.755***	0.697***	−73.865	−32.936	103.436
	(0.020)	(0.010)	(0.011)	(0.008)	(0.008)	(0.008)	(0.022)	(0.106)	(48.730)	(53.480)	(80.684)
FF12 dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes			
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm dummies									Yes	Yes	Yes
Observations	13,116	12,611	13,106	13,116	13,000	13,116	12,500	952	11,251	11,037	11,168
Adjusted R^2	0.085	0.056	0.057	0.063	0.049	0.051	0.106	0.148	0.754	0.831	0.914

This table reports the results of OLS regression of $PEFV - Decile_{i,t}$ on human-capital-related firm characteristics in columns (1) to (8) and future productivity (t+1) on $PEFV - Decile_{i,t}$ in columns (9) to (11). All variables are defined in Appendix A. Industry and year or firm 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)	(9)	(10)	(11)
$OIPS_{i,t}/P_{i,t-1}$	0.623***	0.599***	0.630***	0.559***	0.218***	0.375***	0.315***	0.208***	0.206***	0.556***	0.268***
	(0.042)	(0.045)	(0.042)	(0.038)	(0.075)	(0.083)	(0.122)	(0.078)	(0.077)	(0.040)	(0.062)
$PEPS_{i,t}/P_{i,t-1}$	−0.395***	−0.361***	−0.401***	−0.413***	−0.106	−0.317***	0.160	−0.110	−0.083	−0.408***	−0.148**
	(0.049)	(0.065)	(0.054)	(0.040)	(0.086)	(0.086)	(0.147)	(0.089)	(0.091)	(0.046)	(0.072)
$\boldsymbol{PEFV_{i,t}/P_{i,t-1}}$			**0.036***	**0.026**	**0.038***	**0.027*	**0.055***			**0.026**	**0.043**
			(0.013)	**(0.011)**	**(0.014)**	**(0.015)**	**(0.020)**			**(0.011)**	**(0.018)**
$\boldsymbol{PEFV*PEPS_{i,t}/P_{i,t-1}}$								**0.019**			
								(0.009)			
$\boldsymbol{PEFV\text{-}Decile_{i,t}}$									**0.054**		
									(0.025)		
$EPS_{i,t}/P_{i,t-1}$					1.802***	1.647***	2.802***	1.779***	1.789***		1.762***
					(0.191)	(0.229)	(0.313)	(0.196)	(0.195)		(0.179)
$SGAPS_{i,t}/P_{i,t-1}$						0.099***					
						(0.030)					
$RNDPS_{i,t}/P_{i,t-1}$						1.493***					
						(0.271)					
Intercept	0.944***	0.939***	0.917***	1.111***	1.022***	0.876***	0.824***	1.023***	0.999***	1.024***	1.023***
	(0.059)	(0.061)	(0.060)	(0.018)	(0.016)	(0.020)	(0.061)	(0.017)	(0.026)	(0.021)	(0.019)
FF12 dummies				Yes	Yes	Yes		Yes	Yes	Yes	Yes
Year dummies				Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm dummies							Yes				
Observations	25,976	13,116	13,116	13,116	9,955	6,863	9,955	9,955	9,955	14,286	9,059
Adjusted R^2	0.088	0.087	0.092	0.307	0.365	0.371	0.455	0.361	0.360	0.306	0.381

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 (9) and (11) the sample is further reduced regarding analyst forecast data 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) presents results for multiplying *PEFV* with *PE* per share. Column (9) shows deciles of *PEFV* rescaled to range from zero to one as a further alternative. Column (10) presents the main results for the sample of non-negative *PEFV* firm-years as in Banker et al. (2019). Column (11) presents results for a subsample where high values of *PEFV* (above the upper 5% of the distribution) are treated as measurement errors and excluded from the analysis. 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: Future monthly returns in the year from July to June after portfolio formation

	$PEFV$					PE/TA					$PEFV * PE/TA$				
	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}
Equal-weighted returns:															
Raw returns	.61	.86	.72	.78	.86	.47	.58	.57	.84	.82	.57	.74	.82	.73	.99
$5^{th} - 1^{st}$	Annualized: 3.0%					Annualized: 4.2%					Annualized: 5.1%				
Intercept	**-.07**	**.22***	**.02**	**.13**	**.26****	**-.21****	**-.09**	**-.11**	**.18**	**.32*****	**-.11**	**.06**	**.07**	**.13**	**.42*****
	(.10)	**(.13)**	**(.12)**	**(.11)**	**(.13)**	**(.10)**	**(.11)**	**(.13)**	**(.12)**	**(.11)**	**(.11)**	**(.12)**	**(.08)**	**(.12)**	**(.14)**
$R_{m,\tau} - R_{f,\tau}$	.99***	.99***	.99***	.98***	.97***	.97***	.98***	.99***	.97***	1.03***	1.00***	.96***	.98***	.98***	.99***
	(.02)	(.03)	(.02)	(.02)	(.03)	(.02)	(.03)	(.03)	(.03)	(.03)	(.02)	(.02)	(.02)	(.03)	(.04)
SMB_τ	.66***	.74***	.74***	.75***	.79***	.55***	.69***	.76***	.85***	.90***	.56***	.71***	.83***	.74***	.85***
	(.04)	(.09)	(.08)	(.07)	(.08)	(.08)	(.06)	(.07)	(.06)	(.06)	(.05)	(.08)	(.04)	(.07)	(.08)
HML_τ	.20***	.24***	.23***	.17**	.03	.48***	.27***	.23**	.19***	−.22***	.28***	.28***	.25***	.07	−0.0000
	(.07)	(.09)	(.07)	(.08)	(.10)	(.06)	(.08)	(.10)	(.07)	(.08)	(.06)	(.08)	(.06)	(.09)	(.11)
RMW_τ	.09	.13	.16	.03	.01	.18**	.18**	.14	.11	−.10	.08	.21*	.17**	−.02	−.01
	(.07)	(.11)	(.10)	(.09)	(.09)	(.08)	(.08)	(.09)	(.09)	(.09)	(.08)	(.11)	(.07)	(.10)	(.10)
CMA_τ	.01	−.28*	−.06	−.04	−.04	−.03	.01	.12	.09	.03	.02	−.24*	−.004	−.04	−.16
	(.09)	(.16)	(.11)	(.12)	(.13)	(.09)	(.12)	(.15)	(.10)	(.12)	(.09)	(.14)	(.08)	(.13)	(.15)
Observations	240	240	240	240	240	252	252	252	252	252	240	240	240	240	240
Adjusted R^2	.94	.91	.92	.92	.90	.92	.92	.90	.90	.91	.93	.91	.95	.91	.89
5^{th}- 1^{st}	**.33** (.16) Annualized: 4.0%**					**.54*** (.15) Annualized: 6.4%**					**.53*** (.18) Annualized: 6.4%**				
Value-weighted returns:															
Intercept	−.04	.22	.16	.33**	.41**	−.04	.16	.13	.12	.59***	−.01	.12	.31**	.26	.65***
	(.13)	(.16)	(.17)	(.14)	(.20)	(.12)	(.15)	(.15)	(.19)	(.21)	(.15)	(.16)	(.16)	(.16)	(.21)
5^{th}- 1^{st}	**.45* (.23) Annualized: 5.4%**					**.62*** (.24) Annualized: 7.5%**					**.65** (.25) Annualized: 7.8%**				

This table reports monthly abnormal returns of portfolios built around three different aspects 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 $PEFV$, PE/TA, and $PEFV * PE/TA$. $PEFV$, PE/TA, 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 7: Robustness analyses regarding portfolio returns

		Equal-weighted					Value-weighted				
		1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}
Panel A: Factor model including momentum											
A.1: *PEFV*	*Intercept*	.01	.22*	.06	.18	.34***	−.02	.19	.12	.41***	.39**
		(.10)	(.12)	(.11)	(.11)	(.13)	(.13)	(.16)	(.17)	(.14)	(.20)
	5th- 1st	**.33** (.16) Annualized: 4.0%**					**.41* (.23) Annualized: 4.9%**				
A.2: *PE/TA*	*Intercept*	−.17*	−.01	−.02	.26**	.38***	−.01	.14	.16	.17	.59***
		(.10)	(.10)	(.12)	(.12)	(.11)	(.13)	(.15)	(.14)	(.19)	(.21)
	5th- 1st	**.55*** (.15) Annualized: 6.5%**					**.59** (.24) Annualized: 7.1%**				
A.3: *PEFV*PE/TA*	*Intercept*	−.07	.10	.11	.19	.49***	−.002	.12	.29*	.29*	.62***
		(.11)	(.11)	(.08)	(.12)	(.15)	(.14)	(.15)	(.16)	(.16)	(.20)
	5th- 1st	**.56*** (.18) Annualized: 6.7%**					**.62** (.25) Annualized: 7.5%**				
Panel B: Only countries with highly liquid currencies											
B.1: *PEFV*	*Intercept*	−.13	.23	.02	−.01	.31**	−.08	.15	.13	.24	.34*
		(.11)	(.14)	(.12)	(.12)	(.14)	(.14)	(.16)	(.19)	(.16)	(.19)
	5th- 1st	**.44** (.18) Annualized: 5.2%**					**.42* (.24) Annualized: 5.1%**				
B.2: *PE/TA*	*Intercept*	−.24**	−.12	−.17	.15	.26**	−.03	.11	.01	.02	.56**
		(.11)	(.12)	(.13)	(.13)	(.12)	(.13)	(.15)	(.14)	(.18)	(.22)
	5th- 1st	**.50*** (.16) Annualized: 6.0%**					**.59** (.26) Annualized: 7.1%**				
B.3: *PEFV*PE/TA*	*Intercept*	−.11	.03	.01	.09	.42**	−.08	.08	.24	.18	.70***
		(.11)	(.11)	(.09)	(.13)	(.16)	(.15)	(.17)	(.17)	(.18)	(.23)
	5th- 1st	**.52*** (.20) Annualized: 6.3%**					**.78*** (.27) Annualized: 9.3%**				

This table reports monthly abnormal returns of portfolios for two robustness analyses. Panel A shows results for a factor model supplemented with the momentum factor. Panel B reports results of reducing the sample to firms from countries with highly liquidly traded currencies (i.e., EUR and GBP). 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 8: Long-term portfolio returns

	Year 1					Year 2					Year 3				
	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}
Panel A: Long-term abnormal returns for portfolios formed on *PEFV* quintiles															
Intercept	$-.07$	$.22^{*}$	.02	.13	$.26^{**}$	$-.09$	$.19^{**}$	.01	.07	$.22^{**}$	.07	.03	.09	.10	.21
	(.10)	(.13)	(.12)	(.11)	(.13)	(.10)	(.10)	(.11)	(.11)	(.10)	(.11)	(.10)	(.10)	(.10)	(.14)
5^{th}- 1^{st}	**$.33^{**}$ (.16) Annualized: 4.0%**					**$.30^{**}$ (.14) Annualized: 3.7%**					**.14 (.17) Annualized: 1.7%**				
Panel B: Long-term abnormal returns for portfolios formed on *PE/TA* quintiles															
Intercept	$-.21^{**}$	$-.09$	$-.11$	.18	$.32^{***}$	$-.23^{*}$	$-.005$	$-.11$	.20	$.40^{***}$	$-.18^{**}$	$-.05$	.14	.002	$.44^{***}$
	(.10)	(.11)	(.13)	(.12)	(.11)	(.12)	(.15)	(.12)	(.14)	(.15)	(.08)	(.10)	(.10)	(.12)	(.13)
5^{th}- 1^{st}	**$.54^{***}$ (.15) Annualized: 6.4%**					**$.63^{***}$ (.19) Annualized: 7.6%**					**$.63^{***}$ (.16) Annualized: 7.5%**				
Panel C: Long-term abnormal returns for portfolios formed on *PEFV*PE/TA* quintiles															
Intercept	$-.11$	.06	.07	.13	$.42^{***}$	$-.19^{*}$	.09	.06	.18	$.25^{**}$	$-.09$	.08	.02	.06	$.44^{***}$
	(.11)	(.12)	(.08)	(.12)	(.14)	(.10)	(.09)	(.09)	(.11)	(.12)	(.10)	(.09)	(.10)	(.12)	(.16)
5^{th}- 1^{st}	**$.53^{***}$ (.18) Annualized: 6.4%**					**$.43^{***}$ (.16) Annualized: 5.2%**					**$.53^{***}$ (.18) Annualized: 6.4%**				

This table reports monthly abnormal returns of equal-weighted portfolios up to the third year after portfolio formation following the same procedure as in Table 6. 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: 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 $_{i,t}$	**.111*****			**.104*****	**.089****	**.093****
	(.029)			**(.029)**	**(.042)**	**(.041)**
PE/TA-Quintile $_{i,t}$		**.377*****		**.361*****	**.294*****	**.266*****
		(.037)		**(.039)**	**(.048)**	**(.051)**
PEFV*PE/TA-Quintile $_{i,t}$			**.251*****			
			(.032)			
$Momentum_{-1,0}$	$-.024^{***}$	$-.035^{***}$	$-.025^{***}$	$-.027^{***}$	$-.020^{***}$	$-.024^{***}$
	(.006)	(.006)	(.006)	(.006)	(.007)	(.007)
$Momentum_{-12,-1}$	$.010^{***}$	.005	$.009^{**}$	$.009^{**}$	$.009^{**}$	$.007^{*}$
	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)
$Accruals_{i,t}$	$.251^{*}$	$-.109$	.207	.135	$-.088$	.018
	(.141)	(.228)	(.139)	(.138)	(.198)	(.195)
$AssetGrowth_{i,t}$	$-.194$	$-.516$	$-.211$	$-.220$	$-.342^{*}$	$-.320^{*}$
	(.153)	(.361)	(.152)	(.152)	(.192)	(.192)
$log(BE/ME)_{i,t}$	$.335^{***}$	$.636^{***}$	$.425^{***}$	$.550^{***}$	$.654^{***}$	$.661^{***}$
	(.081)	(.073)	(.081)	(.081)	(.111)	(.103)
$log(ME)_{i,t}$	$.271^{***}$	$.436^{***}$	$.317^{***}$	$.374^{***}$	$.355^{***}$	$.356^{***}$
	(.035)	(.039)	(.036)	(.037)	(.046)	(.046)
$SGA/TA_{i,t}$					.308	.367
					(.315)	(.332)
$RND/TA_{i,t}$					2.317	2.761^{**}
					(1.469)	(1.399)
$EBITDA/TA_{i,t}$					1.812^{**}	1.705^{**}
					(.804)	(.784)
$Intercept$	$-.977^{**}$	-2.434^{***}	-1.599^{***}	-2.489^{***}	-2.390^{***}	-3.071^{***}
	(.390)	(.491)	(0.396)	(0.409)	(.469)	(.429)
Observations	129,935	255,773	129,935	129,935	86,846	86,846
R^2	.258	.248	.259	.262	.278	.088

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 10: Risk factor compensation versus mispricing

Panel A: Risk factor descriptives

Factor	Mean	Median	STD	Calculation period
$PE/TAfactor_{\tau}$	0.39	0.43	2.45	July 1998 to June 2019
$R_{m,\tau}$	0.40	0.60	5.20	July 1998 to June 2019
SMB_{τ}	0.19	0.22	2.12	July 1998 to June 2019
HML_{τ}	0.29	0.27	2.66	July 1998 to June 2019
RMW_{τ}	0.32	0.38	1.67	July 1998 to June 2019
CMA_{τ}	0.24	0.08	2.00	July 1998 to June 2019

Panel B: Risk versus mispricing test

	Dependent variable:	
	$R_{p,\tau}$	
	(1)	(2)
$PE/TA_{p,t}$	**0.715*****	**0.666****
	(0.266)	**(0.303)**
$\beta_{PE/TAfactor_{p,t}}$	**0.288***	**0.298***
	(0.163)	**(0.160)**
$\beta_{market_{p,t}}$	−0.228	0.744
	(0.436)	(0.502)
$\beta_{size_{p,t}}$	−0.251	−0.197
	(0.199)	(0.174)
$\beta_{value_{p,t}}$	−0.406*	0.338
	(0.242)	(0.234)
$\beta_{profit_{p,t}}$	0.295	−0.204
	(0.193)	(0.154)
$\beta_{invest_{p,t}}$	−0.303**	−0.081
	(0.127)	(0.121)
Intercept	1.027**	0.026
	(0.438)	(0.490)
Observations	4,860	4,860
R^2	0.902	0.859

This table reports results from portfolio-level average Fama and MacBeth (1973) regression coefficients for monthly returns regressed on portfolio-level PE/TA and factor loadings following equation (6). The factor mimicking approach used for this table is explained in Appendix D. Column (1) (column (2)) reports results for the equal-weighted (value-weighted) specification. Portfolios are formed based on size, PE/TA, and preformation PE/TA factor loading. The dependent variable in column (1) (column (2)) is equal-weighted (value-weighted) monthly returns from July of year $t+1$ to June of year $t+2$ on the 27 triple-sorted portfolios. $PE/TA_{p,t}$ is the portfolio-level equal-weighted or value-weighted average PE/TA as of fiscal year end t. $\beta_{PE/TAfactor_{p,t}}$ is the June $t+1$ portfolio-level factor loading on the $PE/TAfactor$. $\beta_{market_{p,t}}$, $\beta_{size_{p,t}}$, $\beta_{value_{p,t}}$, $\beta_{profit_{p,t}}$, and $\beta_{invest_{p,t}}$ are the June $t+1$ portfolio-level factor loadings for the five Fama French factors. We ensure that there are at least ten firms per triple-sorted portfolio in each month of a year. This leads to 4,860 portfolio-month-observations (27 portfolios * 15 years * 12 months) from July 2002 to June 2019. *, **, *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.