Does Stock Price Informativeness Affect Labor Investment Efficiency?*

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Abstract

In this paper, we examine whether managers use information included in stock prices when making labor investment decisions. Specifically, we examine whether stock price informativeness affects labor investment efficiency. We find that a higher probability of informed trading (*PIN*) is associated with lower deviations of labor investment from the level justified by economic fundamentals i.e., higher labor investment efficiency. This finding is robust to using alternative proxies for stock price informativeness and labor investment efficiency, when we control for earnings quality and mispricing, and when we address endogeneity issues. Furthermore, we report evidence suggesting that the positive impact of stock price on labor investment efficiency is more (less) pronounced in firms from highly unionized industries and firms facing higher financial constraints (firms from industries that rely more on skilled labor).

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1. Introduction

A growing strand of literature suggests that the information aggregated and transmitted into stock prices via the trading activities of different speculators and investors in the stock markets (Grossman and Stiglitz, 1980; Kyle, 1985), may be used by managers when making investment decisions. Empirical literature provides large support for this point of view. For example, Durnev, Morck and Yeung (2004) show that more informative stock prices help improving investment efficiency. Similarly, Chen, Goldstein, and Jiang (2007) report evidence suggesting that stock price informativeness is associated with higher investment-stock price sensitivity, hence more efficient investment. More recently, Foucault and Frésard (2012), using a large sample of U.S. cross-listings, confirm the findings of Chen et al. (2007). In this paper, we extend the aforementioned strand of literature by examining whether managers use information incorporated in stock prices when investing in human capital. Specifically, we examine whether more informative stock prices are associated with lower deviations of labor investment from the level justified by economic fundamentals i.e., higher labor investment efficiency.

Stock price informativeness may affect labor investment efficiency in three ways. First, stock prices include information that managers do not possess such as information about future investment and growth opportunities, future demand of the firm's products and services, and financing opportunities, which may affect labor investment decisions (Pinnuck and Lillis, 2007; Benmelech, Bergman, and Seru, 2011). Second, more informative stock prices are associated with better external and/or internal monitoring of managers (Ferreira, Ferreira, and Raposo, 2011; Holmström and Tirole, 1993), hence mitigate the empire-building problem (i.e., hiring more employees than required to run profitable projects – over-hiring – or retaining employees who are occupied on non-profitable projects – under-firing). Consequently, more informative stock prices may result on a level of labor investment that is close to the one justified by economic fundamentals – that is, a more efficient labor investment. Third, stock price informativeness is associated with more disclosures and a higher quality of financial reporting (e.g., Jin and Myers, 2006; Haggard, Martin, and Pereira, 2008; Hutton, Marcus, and Tehranian; 2009; Zuo, 2013), which alleviate information asymmetries (Diamond and Verrecchia, 1991), hence mitigate market frictions (Bushman and Smith, 2001; Healy and Palepu, 2001; Lambert, Leuz, and Verrecchia, 2007). Furthermore, empirical research (e.g., Fernandes and Ferreira, 2009) also shows that stock price informativeness helps to reduce the cost of equity, which makes also it easier for firms to finance labor.[1] Consequently, higher stock price informativeness may lead to more efficient investment in labor.

Our research question is important for several reasons. First, we choose to examine the impact of stock price informativeness on labor investment because human capital is one of the important factors of production that determine the firm's output. Second, focusing on labor as a factor of production used by all firms rather than on other types of investment such as research and development (R&D), allows us to test the impact of stock price informativeness on investment across a broad cross-section of firms. Third, labor investment is affected by empire building motivations. Given that, examining the impact of stock price informativeness on labor investment efficiency allows us to further test the hypothesis stating that more informative stock prices alleviate the empire building problems, which leads to over-investment. Finally, focusing on labor investment as one of the first factor of productions to be cut (Pinnuck and Lillis (2007), allows us also to examine how stock price informativeness may limit divestments that are not justified by economic fundamentals (i.e., under-investment).

To empirically test our hypothesis, we follow Pinnuck and Lillis (2007) and estimate the level of labor investment (i.e., the percentage change in the number of employees) justified by economic fundamentals (e.g., profitability, liquidity, leverage, sales growth and losses). Our main proxy for labor investment efficiency is the absolute value of the difference between the observed level of labor investment and the one justified by economic fundamentals. The lower is this difference the higher is labor investment efficiency. To measure the extent of informed trading, hence the degree by which firm-specific information is incorporated into stock prices (i.e., stock price informativeness), we follow Chen et al. (2007) and Ferreira et al. (2011) and use the Probability of Information trading (*PIN*) derived from Easely, Kiefer, and O'Hara's (1996) market microstructure model. A higher value for *PIN* indicates higher probability of informed trading, hence higher stock price informativeness. In robustness tests, we use alternative proxies for stock price informativeness. First, we use Amihud's (2002) illiquidity proxy. Second, we use

[1] Labor cost is not a pure variable cost. In fact, it has a fixed component (e.g., Oi, 1962; Farmer, 1985; Hamermesh and Pfann, 1996) such as hiring, firing, and training costs, and hence requires financing.

firm-specific return variation proxies based on the following models: (i) Fama and French's three-factor model, (ii) Brockman and Yan's (2009) model, and (iii) Jin and Myers's (2006) model.

Using a sample of U.S. firms over the period 1994-2010, we show that a higher probability of informed trading (*PIN*) (i.e., higher stock price informativeness) is associated with lower deviations of labor investment from the level justified by economic fundamentals i.e., higher labor investment efficiency. *PIN* is economically highly significant. In fact, a one standard deviation increase in *PIN* is associated with a 13.1% decrease in labor investment inefficiency. This finding is consistent with the view that managers use the information incorporated in stock prices (e.g., information about future investment and growth opportunities, future relationship with stakeholders, and future financing policies) when investing in human capital. This result is also consistent with the view that stock prices act as a disciplinary mechanism of managers. Specifically, more informative stock prices result in a better monitoring of managers (Ferreira et al., 2011), which alleviates the empire building problem, leading to a more efficient investment in labor. This finding remains robust when we address the endogeneity of *PIN*. Indeed, this result remains qualitatively unchanged when we use firm fixed-effects model and the two-stage instrumental variable approach.

We also show that labor union affects the relationship between stock price informativeness and labor investment efficiency. Firms operating in highly unionized industries may be unable to invest efficiently in labor. Indeed, they face higher adjustment costs (e.g., Jung et al., 2014), which increases the need to finance labor. Furthermore, firms from highly unionized industries suffer from severe information asymmetry problems (e.g., Hillary, 2006). Therefore, we expect that stock price informativeness plays a more important role in enhancing corporate transparency, reducing the cost of financing, and improving labor investment efficiency. Consistent with our prediction, we find that the positive relation between stock price informativeness and labor investment efficiency is more pronounced in firms from highly unionized industries. Additionally, we examine whether the relationship between stock price informativeness is affected by financial constraints. Financial constraints determine labor investment (Benmelech et al., 2011), suggesting that some labor costs are fixed costs (e.g., hiring and training costs), and hence require financing. Therefore, we expect that stock price informativeness plays a more important role in enhancing the ability of firms to finance labor when financial constraints are high. Consistent with this point of view, we find that the positive effect of stock price informativeness on labor investment efficiency is more pronounced in more financially constrained firms. Moreover, we examine whether the relationship between stock price informativeness and labor investment efficiency varies with the firm's degree of reliance on skilled labor. Following Ochoa (2013), Belo and Lin (2014), and Ghaly, Dang, and Konstantinos (2015), among others, we construct an industry-level proxy for the degree of reliance on skilled labor using data from the Occupational Information Network (O*Net) and the Occupational Employment Statistics (OES) program of the Bureau of Labor Statistics. We find that the positive relationship between stock price informativeness and labor investment efficiency is less pronounced in firms from industries that rely more on skilled labor. This finding is consistent with the conjecture that firms facing higher labor adjustment costs are less able to invest efficiently in labor.

In line with prior research on investment efficiency (e.g., Biddle et al., 2009), we split our sample based on whether the difference between the observed labor investment and the one justified by economic fundamentals is positive (i.e., over-investment) or negative (i.e., under-investment). We report evidence suggesting that stock price informativeness helps mitigate all kind of inefficiencies in labor investment. Specifically, we find that stock price informativeness alleviates over-investment and under-investment problems in labor, respectively. We also find that stock price informativeness helps mitigate over-investment and under-investment problems in periods of expected expansion (i.e., over-hiring and under-firing) and expected recession (i.e., under-hiring and over-firing).

We also perform several tests to ensure that our findings are not driven by non-labor investments (i.e., capital expenditures, R&D expenses, advertising expenses, and acquisition expenses). We examine the relationship between on the association between stock price informtiveness and labor investment efficiency when: (i) labor investment and non-labor investment are positively correlated, (ii) labor investment and non-labor investment are negatively correlated, and (iii) the firm has a missing value for non-labor investment. We find that the negative relationship between stock price informativeness and labor investment efficiency is not concentrated in the sub-samples of firms with a positive relationship between non-labor investment and labor investment, suggesting that our findings are not driven by non-labor investments, consistent with the findings of prior studies (e.g., Benmelech et al., 2011; Merz and Yashiv, 2007; Jung et al., 2014; Jung, Kang, Lee, and Zhou, 2015).

We also perform several other robustness tests to ensure the robustness of our findings. We find that our results are robust to the use of alternative proxies of labor investment efficiency as well as alternative definitions of the *PIN* variable. We also find that our results remain qualitatively unchanged after controlling for variables that have been shown to affect labor investment efficiency, particularly earnings management (Jung et al., 2014) and earnings informativeness (Pinnuck and Lillis, 2007). Furthermore, our findings remain robust when control mispricing proxies (i.e., analyst forecast bias, analyst forecast dispersion, and cumulative abnormal returns) that have been shown to affect investment efficiency (e.g., Chen et al., 2007; Bakke and Whited, 2010).

Our paper contributes to the literature in two ways. First, we extend the literature on managerial learning (e.g., Durnev et al., 2004; Chen et al., 2007; Bakke and Whited, 2010; Foucault and Frésard, 2012; Ferreira et al., 2011; Zuo, 2013; De Cesari and Huang-Meier, 2015) by focusing on the investment in human capital. Second, we add to the literature on labor investment (e.g., Pinnuck and Lillis, 2007; Benmelech et al., 2011; Hall, 2013; Faccio and Hsu, 2013; Jung et al., 2014) by examining whether informed trading helps improving labor investment efficiency.

2. Hypothesis development

The managerial learning hypothesis suggests that managers can learn new private information from their stock prices that helps improving their decisions efficiency (Hayek, 1945), hence increases the value of the firm. This private information is aggregated and transmitted into stock prices via the trading activities of different speculators and investors in the stock markets (Grossman and Stiglitz, 1980; Kyle, 1985). This information can be about future investment opportunities (Dow and Gorton, 1997), demand for the firm's product and services, and financing policies (Subrahmanyam and Titman, 1999). It can also take the form of information about relationships with different shareholders and competition with other firms.

Several empirical papers support the managerial learning hypothesis. For example, Durnev et al. (2004) report evidence suggesting that managers are more likely to undertake efficient investment decisions when the firm's stock price conveys more private information from investors. In the same vein, Chen et al. (2007) show that more informative stock prices are associated with higher investment-stock price sensitivity, again supporting the argument that more informative stock prices lead to more efficient investment decisions. This finding is confirmed by Bakke and Whited (2010) who use a different research methodology and Foucault and Frésard (2012) who use a large sample of U.S. cross-listings. Stock price informativeness has been also shown to affect other corporate decisions. In fact, Frésard (2012) shows that higher stock price informativenss improves the efficiency of corporate savings decisions. Similarly, Luo (2005) reports evidence suggesting that mangers use information from the stock markets when finalizing mergers and acquisitions deals. More recently, Zuo (2013) reports evidence suggesting that the information included in stock prices affect forward-looking disclosures. Given the above mentioned arguments, stock price informativeness may affect the investment in labor since it includes information that managers do not possess about the future demand of the firm's products and services, growth opportunities, and financing policies which determines the level of investment in labor (Pinnuck and Lillis, 2007; Benmelech et al., 2011).

The managerial learning hypothesis also suggests that better informed stock prices are associated with better corporate governance (Ferreira et al., 2011; Holmström and Tirole, 1993). Specifically, informative stock prices discipline managers and enhance external monitoring mechanisms. For example, the announcement of non-efficient investments increases the hostile takeover likelihood. Consistent with this point of view, Edmans, Goldstein, and Jiang (2012), using mutual fund redemptions as an instrument for price changes, show that market prices have a strong impact on takeover activity. Informative stock prices may discipline managers since they may be replaced if the takeover succeeds (Holmström and Tirole, 1993). Furthermore, more informative stock prices may be associated with more efficient internal monitoring by the board of directors. Indeed, the board of director's members may learn new information from the stock market; hence better monitor managers. Consistent with this point of view, Ferreira et al. (2011) show that more informative stock prices are associated with less board independence, suggesting that stock price informativeness may replace a disciplinary mechanism such as board monitoring. Therefore, stock price informativeness is associated with better monitoring of managers and may mitigate the empire-building problem. Indeed, empire-building ambitions may induce managers to hire more employees than required on profitable projects or retain employees on unprofitable projects. Stock price informativeness, which is associated with better monitoring of managers, may alleviate this problem, resulting in a level of investment in labor that is close to the one justified by economic fundamentals – that is, a more efficient investment in labor.

Stock price informativeness may also affect labor investment efficiency through market frictions, because labor cost is not solely a variable cost and hence involves adjustment costs and requires financing. Indeed, the literature on labor economics (e.g., Oi, 1962; Farmer, 1985; Hamermesh and Pfann, 1996) argues that labor costs have a fixed component such as the costs associated with training and hiring activities.[2] The existence of market frictions renders the financing of labor costly and may reduce a firm's ability to hire and fire efficiently. The literature provides evidence that stock price informativeness and the quality of financial reporting, as well as disclosures, are positively related. For instance, Jin and Myers (2006) show that idiosyncratic volatility (i.e., stock price informativeness) is higher in countries with more transparent financial markets where informed traders are motivated to gather private information. Moreover, Jin and Myers (2006) find that stocks in less transparent countries with higher R^2 value (lower idiosyncratic volatility) have a higher likelihood of future stock price crashes, that is, of delivering large negative returns – compared to stocks in more transparent countries. In the same vein, Hutton et al. (2009) show that idiosyncratic volatility is negatively related to opacity (measured by earnings management), consistent with the findings of Jin and Myers (2006). They also show that earnings management, which impedes the flow of firm-specific information to capital markets, is associated with higher stock price crash risk. Similarly, Haggard et al. (2008) find a positive relationship between voluntary disclosure and stock price informativeness, also consistent with the findings of Jin and Myers (2006), suggesting that firm transparency improves stock price informativeness. In a more recent work, Zuo (2013) uses annual management forecasts as a proxy for forward-looking disclosures and

[2] The literature (e.g., Chen et al., 2007; Foucault and Frésard, 2012) shows that stock price informativeness enhances the efficiency of physical investment. However, it is not clear whether this result extends to the investment in labor. Indeed, labor, which is viewed in the literature (e.g., Oi, 1962) as a quasi-fixed cost, has lower adjustment costs than physical investment (Dixit and Pindyck 1994). Therefore, it is important to examine whether stock price informativeness improves labor investment efficiency.

tests the hypothesis that managers learn from the information on stock prices held by outside investors when forecasting future earnings. Zuo shows that the association between management forecast revisions and stock price changes over the revision periods is stronger when stock prices are more informative. This result suggests that firms with more informed trading have a stronger revision–return relationship, consistent with the conjecture that managers learn from the private information included in stock prices. In addition, Zuo documents a positive association between this information and the improvement in forecast accuracy.

Improving disclosures and the quality of financial reporting serves to reduce information asymmetries (Diamond and Verrecchia, 1991) and hence mitigate market frictions (Bushman and Smith, 2001; Healy and Palepu, 2001; Lambert et al., 2007). For example, high-quality accounting can mitigate moral hazard problems by facilitating more efficient contracting and enabling more effective monitoring by shareholders and other outsiders. Similarly, high-quality accounting can address adverse selection problems by decreasing the severity of the information asymmetry between managers and security market participants. Because stock price informativenss and the quality of financial reporting are positively related, we expect that it is easier to finance labor when stock prices are more informative. Moreover, empirical research also shows that stock price informativeness helps to reduce the cost of equity (e.g., Fernandes and Ferreira, 2009),[3] which also makes it easier for firms to finance labor.

Based on the discussion above, we expect that higher stock price informativeness leads to more efficient investment in labor.

3. Empirical design

3.1 Stock price informativeness proxies

In line with Chen et al. (2007) and Ferreira et al. (2011), we use the Probability of Information trading (*PIN*) derived from Easely et al.'s (1996) market microstructure model.

[3] Fernandes and Ferreira (2009), using a worldwide sample of 48 countries, show that stock price informativeness mitigates the uninformed investor's risk and is associated with a lower cost of equity.

$$PIN = \frac{\alpha\mu}{\alpha\mu + \varepsilon_B + \varepsilon_S} \tag{1}$$

where α is the probability of informed trading, μ is the daily rate of informed trading occurrence, ε_B is the daily arrival rate of uninformed buy orders, and ε_S is the daily arrival rate of uninformed sell orders. Brown, Hillegeist, and Lo (2004) use intra-day transaction data to estimate α, μ, ε_B, and ε_S and consequently PIN. In this paper, we use Brown et al.'s (2004) continuously updated *PIN* data.[4] The frequency of the used *PIN* data is annual. Brown, Hillegeist, and Lo (2004) use intra-day transaction data over an annual period to estimate α, μ, ε_B, and ε_S in equation (1). This procedure assumes that the parameters are relatively stable over a one-year period. Easley, O'Hara, and Hvidkjaer (2002) argue that this assumption is reasonable because *PIN*s of individual stocks exhibit low variability across years and the cross-sectional distribution of *PIN* is stable across time. Consistent with this argument, they show that annual *PIN*s are quite similar to those estimated over a 60-day period. A higher value for PIN indicates higher probability of informed trading, hence higher stock price informativeness.

3.2 Labor investment efficiency proxy

To examine the impact of stock price informativeness on the efficiency of investment in Labor, we follow Pinnuck and and Lillis's (2007) two steps approach. First, we estimate the expected change in the number of employees based on economic fundamentals using the following model:

$$\begin{aligned} LABOR\_INVEST_{i,t} &= \theta_0 + \theta_1 RET_{i,t} + \theta_2 MV\_RANK_{i,t} + \theta_3 ROA_{i,t} + \theta_4 QUICK\_RATIO_{i,t-1} + \theta_5 LEVERAGE_{i,t-1} \\ &+ \sum_{j=0}^{1}\varphi_j SG_{i,t-j} + \sum_{j=0}^{1}\phi_t \Delta ROA_{i,t-j} + \sum_{j=0}^{1}\alpha_j \Delta QUICK\_RATIO_{i,t-j} + \sum_{j=1}^{5}\beta_j LOSS\_DUMMY_{i,t-1,j} \\ &+ \sum_{j=1}^{48}\alpha_j\gamma_j + \varepsilon_{i,t} \end{aligned} \tag{2}$$

$LABOR\_INVEST_{i,t}$ represents the difference between the number of employees for firm i at year t and $t-1$ scaled by the number of employees for firm i at year $t-1$. Following the

[4] The database is available at http://www.rhsmith.umd.edu/faculty/sbrown/pinsdata.html. See Brown et al. (2004) for a description of the approach used to estimate *PIN* values.

literature (e.g., Pinnuck and Lillis, 2007; Jung et al., 2014), we control for the following variables that affect hiring: First, we control for future expected growth that is not captured by sales growth measures using the annual return for firm i at year t ($RET_{i,t}$). We expect a positive coefficient for $RET_{i,t}$, suggesting that higher future growth is associated with an increase in hiring. Second, we include $MV\_RANK_{i,t}$, the percentile rank of the logarithm of market value for firm i at year t, to control for firm size. Larger firms are more mature and have fewer investment opportunities, and hence have lower hiring levels. However, larger firms are less financially constrained and are therefore better able to increase hiring. Therefore, we do not have a directional prediction on the impact of firm size on hiring. Third, we include $ROA_{i,t}$, $\Delta ROA_{i,t}$, and $\Delta ROA_{i,t-1}$, where ROA is the ratio of net income over total assets to control for the firm's current-year profitability, the current-year change in profitability, and the last-year change in profitability. We expect a positive coefficient for $ROA_{i,t}$ and $\Delta ROA_{i,t-1}$ since profitable firms in the previous and current year are more likely to increase hiring in the next year. The change in ROA in the current year, $\Delta ROA_{i,t}$, may also be positively related to hiring, since an expectation of higher profitability should also increase employment. However, $\Delta ROA_{i,t}$ may be negatively related to hiring, since an increase in hiring, which is associated with an increase in salaries and wages expenses, may reduce net income. Therefore, we do not have a direct prediction for the coefficient of $\Delta ROA_{i,t}$. Fourth, we include $QUICK\_RATIO_{i,t-1}$, $\Delta QUICK\_RATIO_{i,t}$, and $\Delta QUICK\_RATIO_{i,t-1}$, where $QUICK\_RATIO$ is calculated as the ratio of the sum of cash and short-term investments and receivables over current liabilities, to control for the firm's current-year liquidity, the current-year change in liquidity, and the last-year change in liquidity. We expect a positive coefficient for $QUICK\_RATIO_{i,t-1}$ as well as $\Delta QUICK\_RATIO_{i,t-1}$, since firms with a higher quick ratio and those that increased their quick ratio in the previous year are less likely to experience liquidity problems in the current year, and hence are more likely to increase hiring. The change in the current ratio, $\Delta QUICK\_RATIO_{i,t}$, is expected to be positively related to hiring, since an expectation of liquidity improvement should increase hiring. However, $\Delta QUICK\_RATIO_{i,t}$ is also expected to be negatively related to hiring, because the increase in hiring, which increases salaries and wages, may reduce the quick ratio during the same year. Fifth, we control for leverage using $LEVERAGE_{i,t}$, calculated as the ratio of long-term debt for firm i at year t over total assets for firm i at year t. We expect a negative coefficient for $LEVERAGE_{i,t}$ since leverage reduces investment (e.g., Myers, 1977). Sixth, we include $SG_{i,t-1}$ and $SG_{i,t}$ to control for the previous-year and current-year sales growth, where SG represents the difference between sales revenue for the current and previous years scaled by the previous year's sales revenue. We expect a positive coefficient for $SG_{i,t-1}$ since higher sales growth indicates a higher demand for the firm's products and services, which increases hiring. We also expect a positive coefficient for $SG_{i,t}$ because future growth signals an increase in future demand, and hence increases hiring. Finally, we control for loss occurrence using a loss dummy, $LOSS\_DUMMY_{i,t}$, for each 0.005 interval of $ROA_{i,t-1}$ from 0 to -0.025. We expect a negative sign for the loss dummies, since firms experiencing losses are more likely to reduce employment (e.g., Pinnuck and Lillis, 2007). γ_t are industry dummies controlling for industry fixed-effects and $\varepsilon_{i,t}$ is the error term.[5]

We apply the coefficients estimated using equation (2) for each firm-year observation to calculate the predicted value for $LABOR\_INVEST_{i,t}$.[6] Indeed, we estimate equation (2) using all firm-year observations in our sample. The absolute value of the difference between the observed value for $LABOR\_INVEST_{i,t}$ and the predicted value for $LABOR\_INVEST_{i,t}$ using equation (2) (i.e., abnormal change in labor investment), $\left|ABN(LABOR\_INVEST_{i,t})\right|$, is our

[5] The logic for including the level of some variables and the level as well as the change of other variables in equation (2) is as follows: The current-year level and changes are included to control for the expected level and the expected change in the variable. The previous-year level and changes are included to control for the current level and change in the variable. Specifically, we include the current level of stock return and sales growth to proxy for future expected growth and the current level of return on assets to proxy for future profitability. We include the current-year change in return on assets and the quick ratio to control for the increase in future profitability and liquidity. We include the previous-year size, quick ratio, leverage, sales growth, and loss dummies to control for current investment opportunities as well as financial constraints, liquidity, financial risk, and growth. The previous-year change in return on assets and quick ratio are also included to control for the current increase in profitability and liquidity.

[6] The R^2 for this regression is 0.271, which is comparable to that found in related papers (e.g., Jung et al., 2014). We do not have overlapping observations (i.e., more than one observations for each firm in a given year), but we do have overlapping years, since we have panel data, so for each year we have an observation for each firm in our sample.

proxy for the inefficiency of investment in labor. A higher deviation of labor investment from its predicted value based on economic fundamentals indicates lower labor investment efficiency.[7]

To test the relationship between stock price informativeness and labor investment efficiency, we estimate the following regression model:

$$\left|ABN(LABOR\_INVEST_{i,t})\right| = \delta_0 + \delta_1 SPI_{i,t-1} + \delta_2 CONTROLS_{i,t} + \gamma_t + \varepsilon_{it} \quad (3)$$

Following the recent literature on investment efficiency (e.g., Biddle, Hilary, and Verdi, 2009; Jung et al., 2014), we include in $CONTROLS$ the following variables: the natural logarithm of the firm's market value at the beginning of the year ($SIZE_{i,t-1}$) to control firm size, $LEVERAGE_{i,t-1}$ to control for financial risk, the market-to-book ratio ($MB_{i,t-1}$) at the beginning of the year to control for growth opportunities, the ratio of net property, plant, and equipment at year $t-1$ over total assets at year $t-1$ ($NET\_PPE_{i,t-1}$) to control for the extent of investment in fixed assets, $QUICK\_RATIO_{i,t-1}$ to control for liquidity, a dummy variable ($LOSS_{i,t-1}$) equal to one (1) if $ROA_{i,t-1}$ is negative, and zero (0) otherwise to control for economic losses, a dummy variable equal to one (1) if the firm i pays dividends at year $t-1$, and zero (0) otherwise ($DIV\_PAYER_{i,t-1}$) to control for dividend payout, the volatility of cash flow from operations ($CF\_VOL_{i,t}$) and sales revenue ($SALES\_VOL_{i,t}$) over the period from $t-1$ to $t-5$, respectively, to control for operating and sales volatility, the volatility of $LABOR\_INVEST_{i,t}$ over the period from $t-1$ to $t-5$ ($LABOR\_INVEST\_VOL_{i,t}$) in order to control for the volatility of labor investment, and the absolute value of the residuals, $\left|ABN(OTHER\_INVEST_{i,t})\right|$, from the regression of non-labor investment ($OTHER\_INVEST_{i,t}$) on $SG_{i,t}$ to control for non-labor investment efficiency. $OTHER\_INVEST_{i,t}$ is the sum of capital expenditures, acquisition expenditures, and R&D

[7] In line with Pinnuck and and Lillis (2007), we find a positive and significant coefficient for $SG_{i,t}$, $SG_{i,t-1}$, $ROA_{i,t}$, $\Delta ROA_{i,t-1}$, $RET_{i,t}$, $MV\_RANK_{i,t}$, $QUICK\_RATIO_{i,t-1}$ and $\Delta QUICK\_RATIO_{i,t-1}$, respectively. We also find a negative and significant coefficient for $\Delta ROA_{i,t}$, $\Delta QUICK\_RATIO_{i,t}$, $LEV_{i,t-1}$, and all $LOSS\_DUMMY$ variables, respectively.

expenses less the proceeds from the sale of property, plant, and equipment). We also include in $CONTROLS$ the fraction of the firm's shares held by institutional investors at year $t-1$ ($IO_{i,t-1}$) to control for institutional ownership, industry unionization rate ($UNION_{t-1}$) to control for labor protection, and the ratio of the number of employees over total assets at year $t-1$ ($LABOR\_INTENSITY_{t-1}$) to control for labor intensity. The other variables are as previously defined.

3.3 Sample and descriptive statistics

3.2.1 Sample. We collect financial data from *COMPUSTAT*. We also collect firm and market stock returns as well as three factors of Fama-French returns, used to estimate our alternative proxies for stock price informativeness, from *CRSP*. We obtain analyst coverage data from *I/B/E/S* summary files. Additionally, we collect institutional ownership data from Thomson Financial institutional holdings (13f) database and labor union data from Hirsch and Macpherson (2003)'s updated database of Union Membership and Coverage.[8] Data on the probability of informed trading (*PIN*) comes from Brown et al.'s (2004) continuously updated database of PIN estimates. We start with estimating the expected level of investment in labor based on economic fundamentals using Model (2) for all firms listed in *COMPUSTAT* during the period between 1992 and 2010.[9] Then we calculate our proxy of Labor inefficiency as absolute value of the difference between the observed and the expected values of Labor investment. We obtain a sample of 63,558 firm-year observations for the period from 1993 and 2010. Then we merge the estimated labor investment efficiency data with the control variables, institutional ownership, and labor union data. We obtain a sample of 25,938 firm-year observations. After merging the resulting data with Brown et al.'s (2004) continuously updated database of *PIN* estimates and winsorizing all firm-level variables at the 1st and the 99th percentiles to mitigate the effect of outlier observations, we end up with a sample of 21,551 firm-year observations for the period 1994 to 2010.[10]

[8] The database is available at http://www.unionstats.com. See Hirsch and Macpherson (2003) for a description of the approach used to construct this database.
[9] *PIN* data is available for the period between 1993 and 2010. We use *COMPUSTAT* data on the period between 1992 and 2010 to estimate equation (2) because it contains lagged variables.
[10] When we compare the size of the *PIN* sample with the sizes of the nonsynchronocity samples, we find that the latter proxies are slightly larger. In fact, we have 22,348 firm-year observations when we use *SPI1* (Fama and French's three-factor model), 22,619 firm-year observations when we use *SPI2* (Jin and Myers's 2006 model), and 22,542 firm-

Then, we merge estimated Labor investment efficiency data with Brown et al.'s (2004) continuously updated database of *PIN* estimates available for the period from 1993 to 2010. Additionally, we merge the resulting data with data on the control variables outlined in section 3.2. Finally, we winsorize all firm-level variables at the 1st and the 99th percentiles to mitigate the effect of outlier observations. We end-up with a sample of 21,551 firm-year observations for the period from 1994 and 2010.[11]

3.2.2 Descriptive statistics and univariate results. Table 1 reports descriptive statistics on the variables used to estimate equation (3). The average (median) of $|ABN(LABOR\_INVEST_{i,t})|$ is equal to 0.152 (0.099). The average (median) of $PIN_{i,t-1}$ is equal to 0.189 (0.170). These numbers are comparable to those reported in Brown et al. (2004). The descriptive statistics of the control variables are also comparable to related investment studies (e.g., Biddle et al., 2009, and Jung et al. 2014).

[Insert Table 1 about here]

Table 2 reports Pearson correlation coefficients between $|ABN(LABOR\_INVEST_{i,t})|$, $PIN_{i,t-1}$, and the control variables. The correlation coefficients that are significant at the 1% level are shown in bold. Consistent with our hypothesis, we find that $PIN_{i,t-1}$ is significantly and negatively correlated at the 1% level with $|ABN(LABOR\_INVEST_{i,t})|$, suggesting that more informative stock prices lead to more efficient investment in labor. As for the control variables, we report several significant correlations which are consistent with prior related investment literature. In fact, $|ABN(LABOR\_INVEST_{i,t})|$ is negatively and significantly correlated at the 1% level with $SIZE_{i,t-1}$, $DIV\_PAYER_{i,t-1}$ and $IO_{i,t-1}$, indicating that large firms, firms paying dividends, and firms with higher institutional ownership have more efficient investment in labor. $|ABN(LABOR\_INVEST_{i,t})|$ is also positively correlated at the 1% level with $CF\_VOL_{i,t}$,

year observations when we use *SPI3* (Brockman and Yan's 2009 model). However, when we use these proxies our results are qualitatively similar to those obtained when we use the *PIN*, indicating that our findings are not driven by one specific stock price informativeness proxy.

[11] We lost the observations for 1993 because equation (3) includes lagged *PIN*.

$SALES\_VOL_{i,t}$, and $LABOR\_INVEST\_VOL_{i,t}$, implying that firms with more volatile cash flows, sales, and investment in labor have less labor investment efficiency, respectively. Finally, $|ABN(LABOR\_INVEST_{i,t})|$ is positively correlated at the 1% level with $|ABN(OTHER\_INVEST_{i,t})|$, indicating that firms with higher abnormal levels of non-labor investments have lower labor investment efficiency. We generally report low correlation coefficients between *PIN* and our control variables, thus mitigates multicollinearity concerns that could affect our regression results.

[Insert Table 2 about here]

4. Empirical results

4.1 Main evidence

Table 3 reports the OLS results obtained by regressing our proxy for labor investment efficiency on *PIN*. In all models, we control for firm-level and year fixed-effects. The results reported in Model 1, our basic regression, provide evidence that supports our hypothesis, suggesting that more informative stock prices are associated with a level of investment in labor that is close to the one justified by economic fundamentals i.e., higher labor investment efficiency. To be precise, we find that the coefficient of $PIN_{i,t-1}$ is negative and statistically significant at the 1% level, suggesting that managers use the information incorporated in stock prices (e.g., information about future investment and growth opportunities, future relationship with stakeholders, and financing policies) which leads to more efficient investment in labor. An alternative explanation of our finding is that informative stock prices act as a disciplinary mechanism of managers, hence better monitoring, which alleviates the empire building problem, resulting in a more efficient investment in labor. $PIN_{i,t-1}$ is economically highly significant. It shows conclusively that a one standard deviation increase in stock price informativeness is associated with a 13.6% decrease in labor investment inefficiency.[12]

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[12] The sample average value $|ABN(LABOR\_INVEST_{i,t})|$ is 0.152. The coefficient for $PIN_{i,t-1}$ is equal to -0.209 and its standard deviation is equal to 0.099. A one standard deviation increase in $PIN_{i,t-1}$ is associated with a 13.6% decrease in labor investment inefficiency (-0.209*0.099/0.152)=-0.136).

The rest of the Models of Table 3 reports the results of estimating regression (3) with different approaches to ensure the robustness of our finding. One potential concern is that PIN and labor investment efficiency may be jointly determined by unobservable factors. We use the lagged value of *PIN* as an explanatory variable instead of its current value, which helps addressing this issue. We further address this concern using the firm-fixed effects approach (Model 2), the two-stage least squares approach (Models 3 and 4), and the dynamic GMM approach (Model 5). The results of Model 2 show that coefficient for $PIN_{i,t-1}$ is still negative and significant at the 1% level, corroborating our earlier finding. $PIN_{i,t-1}$ is also still highly economically significant. In fact, moving $PIN_{i,t-1}$from its first quartile to its third quartile is associated with a 13.1% decrease in labor investment efficiency. Model 3 reports the results of the first-stage in which we predict PIN on the basis of instruments along with the other independent variables used in our basic regression (Model 1 of Table 3). We use the natural logarithm of one plus the number of analysts following the firm ($ACOV$) as well as turnover ratio ($TURNOVER$), calculated as the ratio of the number of shares traded over the number of shares outstanding, as instruments for PIN. Piotroski and Roulstone (2004) and Chan and Hameed (2006) show that higher analyst coverage is associated with more synchronous stock prices with the market, i.e., less informative stock prices. Ferreira et al. (2011) also report evidence suggesting that share turnover is associated with lower stock price informativeness. These findings are consistent with the conjecture that firms with higher analyst coverage and greater trading activity have more uninformed order flow, i.e., lower stock price informativeness, respectively. Given that, we expect a negative coefficients for both $ACOV$ and $TURNOVER$. The results, reported in Model 3 of Table 3, show that $ACOV$ and $TURNOVER$ loads negative and significant at the 1% level, consistent with our predictions.[13] In the second stage, we use the first-stage fitted values as instruments for PIN. The results, reported in Model 4 of Table 2, show that the coefficient for PIN remains negative and significant at the 1% level, again supporting our earlier finding. Model 5 reports the results of the dynamic panel GMM approach proposed by Wintoki, Linck, and Netter (2012), which incorporates the dynamic relation between stock price investment and labor investment efficiency while taking

[13] To validate our choice of instruments for *PIN*, we follow Larcker and Rusticus (2010, page 190) and perform an over-identifying restriction test, that is, we regress the residuals of the second stage on the exogenous variables (i.e., *ACOV*, *TURNOVER*, and the control variables). We find that the explanatory variables are jointly not significant, suggesting that *ACOV* and *TURNOVER* is exogenous.

into consideration other sources of endogeneity.[14] The results of this model show that the negative coefficient of *PIN* preserves and is significantly and economically different from zero, further confirming our previous finding. Additionally, we use Fama and MacBeth's (1973) approach as well as median (least absolute value regression) in Models 6 and 7 to ensure that our findings are not affected by potential outlier problems and cross-sectional error correlation. The coefficient for $PIN_{i,t-1}$ remains negative and significant at the 1% level, corroborating our earlier finding.

We report several significant relations between the control variables and our proxy for labor investment efficiency. The coefficients for $SIZE_{i,t-1}$, $DIV\_PAYER_{i,t-1}$ and $IO_{i,t-1}$ are negative and significant at the 1% level, across all specifications, suggesting that large firms, dividend payers firms, and firms with higher institutional ownership invest more efficiently in labor. Additionally, we find a positive and generally significant coefficients for $LEV_{i,t-1}$, $QUICK\_RATIO_{i,t-1}$, $LOSS_{i,t-1}$, $LABOR\_INVEST\_VOL_{i,t}$, implying that firms with higher leverage, higher liquidity, losses and higher labor investment volatility have less labor investment efficiency., respectively. Finally, we find that $\left|ABN(OTHER\_INVEST_{i,t})\right|$ is positive and significant at the 1% level, across all specifications, implying that other investments and labor are positively related due to the complementarity between these two types of investment. This finding suggests that the positive relation between stock price informativeness and labor investment efficiency is not entirely driven by the positive impact of stock price informativeness on the efficiency of other investments. This finding is consistent with those of Benmelech et al. (2011), who show that financial constraints affect labor investment even after controlling for capital investments, Merz and Yashiv (2007), who document that labor investment has an incremental effect on firm value beyond capital investments, and Jung, Kang, Lee, and Zhou (2015), who find that the relation between labor-friendly regulations (i.e., laborism) is not driven by the impact of laborism on the efficiency of other investments.

[Insert Table 3 about here]

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[14] Wintoki, Linck and Netter (2012) show that the estimator of dynamic panel generalized method of moments (GMM) provides the valid and powerful instruments that address unobserved heterogeneity and simultaneity using the example of board structure and firm performances.

4.2 Alternative proxies for stock price informativeness

We use several other stock price informativeness proxies as robustness. First, we use Amihud's (2002) illiquidity proxy. The illiquidity ratio is defined as the annual average of the ratio of the daily absolute stock return over the daily transaction volume (multiplied by 10^6).

$$ILLIQ_{i,t} = \frac{1}{D_{i,t}} \sum_{\tau=1}^{D_{i,t}} \frac{|r_{i,\tau}|}{VOLD_{i,\tau}} \tag{4}$$

where $r_{i,\tau}$ is the stock return of firm i at day τ, $VOL_{i,\tau}$ is the dollar volume of firm i at day τ, and $D_{i,t}$ is the number of transactions of firm i's stock at year t. This measure gives the absolute percentage change of stock price per dollar trading volume, hence proxies the impact of trades on price. A higher value of $ILLIQ_{i,t}$ indicates more informed trading (Kyle, 1985), hence more informative stock prices (Ferriera et al., 2011, and Frésard, 2012).

Third, we use three different firm-specific return variation proxies of nonsynchronicity (i.e., stock price informativeness). These measures are widely used as proxies for stock price informativeness. They measure idiosyncratic volatility (i.e., the component of stock return variation that is not explained by market and industry return). A higher idiosyncratic volatility reflects lower correlation between stock returns and market as well as industry returns, indicating that stock prices are more likely to reflect firm-specific information (French and Roll, 1986; Roll, 1988), hence stock prices are less synchronous. Therefore, it indicates higher stock price informativeness (Morck, Yeung, and Yu, 2000).[15] *Firstly*, we estimate our measure of firm-specific variation using Fama and French three-factor model. Specifically, we regress the difference between weekly stock return and the risk free rate (i.e., excess return) of each firm in our sample on the three factors from the model of Fama and French:

$$RET_{it} - R_{f_t} = \alpha_i + \beta_{1i} RM_t + \beta_{2i} SMB_t + \beta_{3i} HML_t + \varepsilon_{it} \tag{5}$$

[15] *PIN* is also an important and widely used proxy for stock price informativeness. In fact, Chen et al. (2007) state: "As *PIN* directly estimates the probability of informed trading, it is conceptually a sound measure for the private information reflected in stock price" (p. 627). A higher *PIN* indicates higher probability of informed trading, hence a greater amount of private information reflected in stock prices. Therefore, consistent with the literature (e.g., Chen et al., 2007; Ferreira et al., 2011), we use both the *PIN* and the nonsynchronicity proxies as the main proxies for stock price informativeness. We report the results using *PIN*, for the sake of space, but all the results reported in our paper are robust to the use of the nonsynchronicity proxies.

where RET_{it} is stock return for firm i at week t, R_{f_t} is the risk free rate at week t, RM_t is equal to the value-weighted excess market at week t, SMB_t is the small-minus-big size factor return at week t, HML_t is the high-minus-low book-to-market factor return at week t, and ε_{it} is an error term. The logistic transformation of the ratio of idiosyncratic volatility to total volatility ($1-R^2$) estimated using equation (5), $\log(\frac{1-R^2}{R^2})$ is our first proxy for stock firm-specific return variation ($SPI1$). A higher value for $SPI1$ indicates higher firm-specific stock return variation i.e., more informative stock prices.

Secondly, we estimate our measure of firm-specific variation using Brockman and Yan's (2009) model. We regress the weekly stock return of each firm in our sample on the current and previous week's value-weighted market return as well as the current and previous week's value-weighted industry return:

$$RET_{it} = \alpha_i + \beta_{1i}MARKET\_RET_{i,t} + \beta_{2i}MARKET\_RET_{i,t-1} + \beta_{3i}INDUST\_RET_{i,t} + \beta_{4i}INDUST\_RET_{i,t-1} + \varepsilon_{it} \quad (6)$$

where $MARKET\_RET_{i,t}$ is value-weighted market return at week t. $INDUST\_RET_{i,t}$ is equal to the value-weighted return for the industry to which firm i belongs at week t. Industry is based on Fama and French's (1997) classification. The rest of the variables are as previously defined. The logistic transformation of the ratio of idiosyncratic volatility to total volatility estimated using equation (6) is our second proxy for stock firm-specific return variation ($SPI2$).[16]

Thirdly, we estimate our measure of firm-specific variation using Jin and Myers's (2006) model. We regress the weekly stock return of each firm in our sample on the current week, previous week, two weeks back, one week ahead and two weeks ahead value-weighted market return:

$$RET_{it} = \alpha_i + \beta_{1i}MARKET\_RET_{i,t} + \beta_{2i}MARKET\_RET_{i,t-1} + \beta_{3i}MARKET\_RET_{i,t-2} + \beta_{4i}MARKET\_RET_{i,t+1} + \beta_{5i}MARKET\_RET_{i,t+2} + \varepsilon_{it} \quad (7)$$

[16] The nonsynchronicity measure used by Chen et al. (2007) is obtained by regressing the firm's weekly stock return on the current week value-weighted market return as well as the current week value-weighted industry return. This measure is very close to our second nonsynchronicity measure (*SPI2*). The only difference between Chen et al.'s (2007) nonsynchronicity measure and *SPI2* is that we add the previous week value-weighted market return and industry return to Chen et al.'s (2007) market model, in line with Brockman and Yan (2009). Lagged returns are introduced to account for the fact that market and industry information may be incorporated into stock prices with a delay.

the variables are as previously defined. The logistic transformation of the ratio of idiosyncratic volatility to total volatility estimated using equation (7) is our third proxy for stock firm-specific return variation ($SPI3$).

The results for the Amihud's (2002) illiquidity measure are reported in Model 1 of Table 4. We find that the coefficient for $ILLIQ_{i,t-1}$ is negative and significant at the 1% level, corroborating our previous finding and suggesting that firms are more likely to invest efficiently in labor when price contains more private information. $ILLIQ_{i,t-1}$ is also economically highly significant. Indeed, a one standard deviation increase in $ILLIQ_{i,t-1}$ is associated with a 5.78% decrease in labor investment inefficiency. The results for our first proxy for firm-specific stock return variation are reported in Model 2 of Table 4. We find that the coefficient of $SPI1_{i,t-1}$ is negative and significant at the 1% level, suggesting that firms whose stock returns are less synchronized with the market invest more efficiently in labor. $SPI1_{i,t-1}$ is also economically highly significant. In fact, a one standard deviation increase in $SPI1_{i,t-1}$ decreases labor investment inefficiency by 4.93%. The results for our second proxy and third proxy for firm-specific stock return variation are reported in Models 3 and 4 of Table 4, respectively. We find that the coefficients of $SPI2_{i,t-1}$ and $SPI3_{i,t-1}$ are negative and significant at the 1% level, respectively. These results again suggest that a high degree firm-specific stock return variation is associated with more efficient labor investment.

[Insert Table 4 about here]

4.3 The role of labor union and financial constraints

In this section, we examine the impact of labor union and financial constraints on the relationship between stock price informativeness and labor investment efficiency, respectively. In Models 1 and 2, we separately include these variables as well as interaction terms between stock price informativeness and these variables. In Model 1, we examine how labor union measured by the industry-level of unionization (*UNION*) affects the association between *PIN* and labor investment efficiency. Firms are less able to hire and fire efficiently when labor unions are strong. In fact, wages are stickier and layoffs are more costly in highly unionized industries (e.g., Chen et al., 2011). Therefore, firms face higher adjustment costs when labor unions are strong (e.g., Jung et al., 2014), which increases their need to finance labor. Stock price informativeness is associated with more disclosures and a higher quality of financial reporting (e.g., Jin and Myers, 2006; Haggard et al., 2008; Hutton et al., 2009; Zuo, 2013), which alleviates information asymmetries (Diamond and Verrecchia, 1991) and hence mitigates market frictions (Bushman and Smith, 2001; Healy and Palepu, 2001; Lambert et al., 2007). Furthermore, empirical research (e.g., Fernandes and Ferreira, 2009) also shows that stock price informativeness helps to reduce the cost of equity, which makes also it easier for firms to finance labor. Moreover, firms from highly unionized industries have severe information asymmetry problems (e.g., Hillary, 2006). Consequently, we expect that higher stock price informativeness plays a more important role in mitigating information asymmetry problems and reducing financing costs when firms face strong labor unions. Hence, the positive impact of stock price informativeness on labor investment efficiency is expected to be more pronounced in the sub-sample of firms from highly unionized industries. The results reported in Model 1 of Table 5 show that the coefficient for $PIN_{i,t-1}*UNION_{i,t-1}$ is negative and highly significant, suggesting that stock price informativeness is associated with a lower $\left|ABN(LABOR\_INVEST_{i,t})\right|$ – that is, higher labor investment efficiency in firms from highly unionized industries, consistent with our prediction.

In Model 2 we examine the impact of financial constraints on the association between stock price informativeness and labor investment efficiency. Benmelech et al. (2011) show that financial constraints determine labor investment. This finding is consistent with the argument that labor costs are not pure variable costs, hence require financing. Indeed, several labor costs are fixed costs such as hiring and training costs (e.g., Oi, 1962; Hamermesh, 1993). Therefore, we expect that more financially constrained firms are less able to invest efficiently in labor (e.g., Benmelech et al., 2011). Stock price informativeness is associated with higher corporate transparency and reduced financing costs, so it also makes it easier for firms to finance labor. Therefore, we expect that stock price informativeness plays a more important role in enhancing labor investment efficiency when firms face higher financial constraints. To test this hypothesis, we use external financing dependence (*EF*) calculated as the industry-median value of the difference between capital expenditures and cash flow from operations scaled by capital expenditures as a proxy for financial constraints, in line with Foucault and Frésard (2012). A higher value of *EF* for a specific industry indicates that a firm belonging to this industry is more likely to be highly financially constrained.[17] The results reported in Model 2 of Table 5 show that the coefficient for $PIN_{i,t-1}*EF_{i,t-1}$ is negative and significant at the 1% level, consistent with our prediction and suggesting that the positive relation between stock price informativeness and labor investment efficiency is more pronounced in more financially constrained firms.

[Insert Table 5 about here]

4.4 Over-investment versus under-investment

We extend our previous analysis by separately examining the impact of stock price informativeness on labor investment efficiency for the sub-sample of firms for which the observed labor investment is higher than expected (over-investment) and the sub-sample of firms for which the observed labor investment is lower than expected (under-investment). The results for the over-investment sub-sample are reported Panel A of Table 6. The results of the total over-investment sub-sample firms are reported in Model 1. We find that the coefficient for $PIN_{i,t-1}$ is negative and significant at the 1% level, suggesting that more informative stock prices help mitigate over-investment problems in labor, also consistent with the conjecture that informative stock prices help mitigate the empire building problem. We split our over-investment sub-sample based on whether the expected level of labor investment (i.e., estimated using equation (2)) is positive (over-hiring) or negative (under-firing). The results of the over-hiring sub-sample are reported in Model 2 of Table 6. We find that the coefficient for $PIN_{i,t-1}$ is negative and significant at the 1% level, suggesting that stock price informativeness helps mitigate over-investment problems in period of expected expansion. The results of the under-firing sub-sample are reported in Model 3 of Table 6. We find that the coefficient for $PIN_{i,t-1}$ is negative and highly significant, suggesting that stock price informativeness also mitigates over-investment problems in period of expected recession. As we can also see, the coefficient for

[17] We find that the coefficient for $EF_{i,t-1}$ is positive and significant at the 1% level, suggesting that firms that are more financially constrained are less likely to invest efficiently in labor, consistent with our prediction. This finding is robust to the use of alternative proxies for financial constraints (i.e., Kaplan and Zingales's index (*KZ*) and a credit rating dummy from *COMPUSTAT* – that is, a variable equal to one if a firm has an S&P long-term domestic issuer credit rating and zero otherwise).

$PIN_{i,t-1}$ is higher in absolute value for the over-hiring sub-sample than for the under-firing sub-sample, suggesting that stock price informativeness plays a greater role in mitigating over-hiring problems than in under-firing problems. This result highlights the importance of stock price informativeness in mitigating the empire-building problem.

The results for the under-investment sub-sample are reported in Panel B of Table 6. The results of the total under-investment sub-sample firms are reported in Model 4. We find a negative and significant coefficient for $PIN_{i,t-1}$ at the 1% level, suggesting that more informative stock prices also mitigate under-investment problems in labor. Also, when we compare the coefficient of $PIN_{i,t-1}$ for the under-investment and over-investment sub-samples, we observe that it is higher in the under-investment sub-sample, suggesting that informative stock prices play a greater role in mitigating under-investment problems. Additionally, we split our under-investment sub-sample based on whether the expected level of labor investment is positive (under-hiring) or negative (over-firing). The results of the under-hiring (over-firing) sub-sample are reported in Model 5 (6) of Table 6. As we can observe, $PIN_{i,t-1}$ is negative and significant in Models 5 and 6, suggesting that informative stock prices help mitigate under-investment in periods of expected expansion and expected recession, respectively. Moreover, we find that the coefficient for $PIN_{i,t-1}$ is higher in absolute value for the under-hiring sub-sample than for the over-firing sub-sample, suggesting that informative stock prices play a more important role in mitigating under-hiring problems. Finally, when we compare the coefficient for $PIN_{i,t-1}$ in the under-hiring and over-hiring sub-samples (i.e., the one with the highest $PIN_{i,t-1}$ in the over-investment category), we find that is higher in the under-hiring sub-sample, supporting our previous finding that stock price informativeness plays a greater role in mitigating under-investment problems.

Collectively, our results suggest that informative stock prices help alleviating all kind of inefficiencies in labor investment, hence are associated with a level of labor investment that is close to the one justified by economic fundamentals.

[Insert Table 6 about here]

4.5 High- versus low-skilled labor

We argue that the relation between stock price informativeness and labor investment efficiency varies with the degree of the firm's use of skilled labor. Indeed, labor adjustment costs (e.g., firing, hiring, and training) are higher in firms that rely more on skilled labor (e.g., Oi, 1962; Hamermesh and Pfann, 1996; Dixit, 1997). Therefore, firms using more skilled labor have a greater need to finance labor, and hence are less able to invest efficiently in labor. We use the industry average number of employees working in occupations with a JobZones index equal to 4 or 5 as a proxy for the degree of reliance on skilled labor, in line with Ochoa (2013), Belo and Lin (2014), and Ghaly, Dang, and Konstantinos (2015). We collect JobZones data from Occupational Information Network (O*Net), available at http://www.onetonline.org/find/zone. We gather the data on the number of employees by occupation from the Occupational Employment Statistics (OES) program of the Bureau of Labor Statistics. We re-run our basic regression (Model 1 of Table 3) separately for the sub-sample of firms from industries that rely more on skilled labor (*HIGH_SKILLED*) versus those that rely less on skilled labor (*LOW_SKILLED*). As can be seen in Models 1 and 2 of Table 7, the coefficient for $PIN_{i,t-1}$ is negative and significant at the 1% level in both sub-samples, but is lower in absolute value for the *HIGH_SKILLED* sub-sample. This finding suggests that the positive relation between stock price informativeness and labor investment efficiency is less pronounced in firms belonging to industries that rely more on skilled labor, consistent with the conjecture that such firms have higher labor adjustment and hence are less able to invest efficiently in labor. In the remainder of Table 7 we re-run Models 1 and 2 separately for the over-investment and under-investment sub-samples. The results for the over-investment sub-sample are reported in Models 3 and 4 of Table 7. As can be seen, the coefficient for $PIN_{i,t-1}$ is again lower for the *HIGH_SKILLED* sub-sample, suggesting that the role played by stock price informativeness in mitigating labor over-investment problems is less important in firms belonging to industries that rely more on skilled labor. As can also be seen in Models 3 and 4 of Table 7, the coefficient for $PIN_{i,t-1}$ is lower for the *HIGH_SKILLED* sub-sample, implying that the effect of by stock price informativeness on under-investment in labor is weaker in firms that rely more on skilled labor.

[Insert Table 7 about here]

4.6 Alternative proxies for labor investment efficiency

We use alternative labor investment efficiency proxies to ensure the robustness of our findings. First, we use the difference between the observed value of labor investment and the industry-median value of labor investment, in line with Cella (2010). Second, we use the absolute value of the difference between the observed value for labor investment and the residuals from the regression of the observed value of labor investment on sales growth (*SG*), in line with Biddle et al. (2009), as an alternative proxy for labor investment efficiency. Third, we augment regression (2) with several additional variables.[18] We then re-calculated the absolute value of abnormal labor investment as the difference between the observed labor investment and the residuals form the augmented version of regression (2). Finally, we estimate equation (2) separately for each industry of our sample. Then, we calculate our proxy for labor investment efficiency as the difference between the observed value of labor investment and the residuals from the industry-level version of regression (2). The results reported in Models from 1 to 4 in Table 8 show that the coefficient for $PIN_{i,t-1}$ is still negative and significant at the 1% level, again supporting our earlier findings.

In the remainder of this section we examine the role of stock price informativeness in determining wages instead of hiring and firing. Indeed, we agree that stock price informativeness affects not only the number of employees, but also their salaries. It is argued in the literature (e.g., Deirynck, Landsman, and Renders, 2012; Hall, 2013; Prabowo, Hooghiemstra, and Veen-Dirks, 2015) that labor costs behave asymmetrically. Specifically, it is shown that labor costs are more sensitive to an increase than to a decrease in activity. In fact, it is documented that labor costs increase more when activity increases than they decrease when activity decreases. A strand of literature shows that managers' incentives determine labor cost behavior. For instance, Deirynck et al. (2012) show that empire-building incentives lead managers to increase upward adjustment of labor costs due to increases in activity more and/or decrease downward adjustment of labor costs due to decreases in activity less. In a related paper, Hall (2013) shows that upward labor cost adjustments increase more quickly and downward labor cost adjustments decrease more slowly in public banks, characterized by a

[18] The additional control variables are the logarithm of GDP per capita (*LGDPC*), industry unionization rate (*UNION*), capital expenditures (*CAPEX*), research and development expenses (*XRD*), acquisition expenses (*AQC*), and lagged value of observed labor investment, in line with Pinnuck and Lillis (2007).

higher degree of separation of control and ownership, and hence are more affected by the empire-building problem than private firms. Similarly, Prabowo et al. (2015) report evidence suggesting that labor costs are stickier in state-owned-enterprises (SOEs) characterized by weak corporate governance. As discussed above, more informative stock prices are associated with better monitoring of managers (Ferreira et al., 2011), which alleviates the empire-building problem. Therefore, we expect that labor cost stickiness decreases with stock price informativeness. To test this point of view, we follow Chen, Lu, and Sougiannis (2012) and Prabowo et al. (2015) and use the following model:

$$\begin{aligned} Log\left(\frac{LABOR\_COST_{i,t}}{LABOR\_COST_{i,t-1}}\right) &= \alpha_0 + \alpha_1 Log\left(\frac{REV_{i,t}}{REV_{i,t-1}}\right) + \alpha_2 DECR_{i,t} * Log\left(\frac{REV_{i,t}}{REV_{i,t-1}}\right) \\ &+ \alpha_3 DECR_{i,t} * SPI_{i,t} * Log\left(\frac{REV_{i,t}}{REV_{i,t-1}}\right) + \alpha_4 DECR_{i,t} * CONTROLS_{i,t} * Log\left(\frac{REV_{i,t}}{REV_{i,t-1}}\right) \\ &+ \alpha_6 * SPI_{i,t} + \alpha_7 * CONTROLS_{i,t} + \gamma_t + \varepsilon_{it} \end{aligned} \tag{8}$$

where $LABOR\_COST_{i,t}$ is staff expense from Compustat, which represents wages and other benefits paid to employees and officers; $REV_{i,t}$ is total revenue; $DECR_{i,t}$ is a dummy variable equal to one if total revenue decreased from the previous year and zero otherwise; $SPI_{i,t}$ is our main stock price informativeness proxy, namely *PIN*; $CONTROLS_{i,t}$ include the following control variables: asset intensity ($AI_{i,t}$), defined as the ratio of total assets over total revenue; whether the firm had a decrease in revenue during the current and the previous year ($SUCC\_DECR_{i,t}$); whether the firm reported a loss in the previous year using a dummy variable ($LOSS_{i,t-1}$) equal to one (1) if $ROA_{i,t-1}$ is negative, and zero (0) otherwise; institutional ownership ($IO_{i,t}$); industry unionization rate ($UNION_t$); γ_t are industry and year dummies controlling for industry and year fixed-effects; $\varepsilon_{i,t}$ is the error term. We expect that α_1 is positive and α_2 is negative, consistent with prior research (e.g., Anderson Banker, and Janakiraman, 2003; Chen et al., 2012; Prabowo et al., 2015) and suggesting that labor costs are sticky. The results of estimating equation (8), which reduces our sample size, are reported in Model 5 of Table 8. They indicate that the coefficient for $DECR_{i,t} * SPI_{i,t} * Log\left(\frac{REV_{i,t}}{REV_{i,t-1}}\right)$ is positive and significant at the 1% level, suggesting that that more informative stock prices alleviate the empire-building problem and hence decrease labor cost stickiness. Collectively, our results indicate that our finding that stock price informativeness enhances labor investment efficiency is not driven by a specific labor investment proxy.

[Insert Table 8 about here]

4.7 The role of non-labor investments

Stock price informativeness may indirectly affect labor investment through its impact on other investments such as capital expenditures (*CAPX*) and R&D expenses (*XRD*). For instance, growing firms usually increase both physical and labor investment. Therefore, the positive relation between stock price informativeness and labor investment efficiency may be driven by the positive relation between stock price informativeness and the efficiency of other investments (e.g., Chen et al., 2007) due to the complementarity between these investments and labor. However, as discussed above, stock price informativeness may affect labor investment efficiency through market friction, because labor cost is not solely a variable cost and hence it involves adjustment costs (e.g., Oi, 1962; Farmer, 1985; Hamermesh and Pfann, 1996) and requires financing. Specifically, stock price informativeness is associated with higher corporate transparency and lower financing costs, which makes it easier for firms to finance labor and thus enhances labor investment efficiency. In order to rule out the possibility that the positive association between stock price informativeness and labor investment efficiency is driven by other investments, as a first step we control all our regressions for the non-labor investment efficiency using the absolute value of abnormal non-labor investment. In this section, we further address this issue by examining the impact of non-labor investments (i.e., capital expenditures (*CAPX*), R&D expenses (*XRD*), advertising expenses (*XAD*), and acquisitions (*AQC*)) on the association between stock price informativeness and labor investment efficiency. We divide our sample into three sub-samples: (i) firms for which an increase (decrease) in labor investment is accompanied by an increase (decrease) in non-labor investment (i.e., a positive relationship between labor and non-labor investment); (ii) firms for which an increase (decrease) in labor investment is accompanied with a decrease (increase) in non-labor investment or a decrease in labor investment, and (iii) firms with a missing value for non-labor investment (i.e., firms without *CAPX* or *XRD* or *XAD* or *AQC*). Panel A of Table 9 reports the results for the sub-samples based on the relationship between *CAPX* and labor investment. We find that the negative relationship between stock price informativeness and labor investment efficiency is not concentrated in the sub-sample of firms with a positive relationship between *CAPX* and labor investment (i.e., Model 1). In fact, we also find negative and significant coefficients for $PIN_{i,t-1}$ in Models from 2 and 3. As can be seen, the coefficient for $PIN_{i,t-1}$ is the lowest in absolute value for the sub-sample of firms with zero *CAPX*. However, it is the highest in absolute value for the sub-sample with a positive correlation between *CAPX* and labor investment. These results suggest that stock price informativeness plays a more important role in increasing hiring when the increase in physical investment is higher. Panel B of Table 9 reports the results for the sub-samples based on the relationship between *XRD* and labor investment. We find that the coefficient for $PIN_{i,t-1}$ is negative and significant at 1% not only in Model 4 (i.e., the sub-sample of firms with a positive relationship between *XRD* and labor investment), but also in Models 5 and 6. As can also be seen, the coefficient for $PIN_{i,t-1}$ for the sub-sample with a positive correlation between *XRD* and labor investment is higher than that for the sub-sample with negative correlation, suggesting that stock price informativeness helps firms to increase hiring due to an increase in R&D investment. Panel C of Table 9 reports the results for the sub-samples based on the relationship between *XAD* and labor investment. We find that the coefficient for $PIN_{i,t-1}$ is again negative and significant not only in the sub-sample with a positive relationship between *ACQ* and labor investment (i.e., Model 7) but also at the 1% level in Models 8 and 9. Finally, Panel D of Table 9 reports the results based on the relationship between *AQC* and labor investment. As can be observed, $PIN_{i,t-1}$ is negative at the 1% level in Models 10, 11, and 12, confirming that the negative relationship between stock price informativeness and labor investment is not concentrated in the sub-sample of firms for which labor investment is positively correlated with *AQC*. Also, we find that the coefficient for $PIN_{i,t-1}$is lowest for the sub-sample with zero *AQC* and highest for the sub-sample with positive correlation between *AQC* and labor investment, suggesting that the role of stock price informativeness in increasing hiring is more important when the need to increase acquisitions is high.

We perform an additional test to ensure that our findings are not entirely driven by other investments. Specifically, we repeat our previous analysis using the total investment in capital

(*INVEST_ OTHER*) instead of using individual components. *INVEST_ OTHER* is the sum of capital expenditures (*CAPX*), acquisition, and R&D expenses (*XRD*) less proceeds from the sale of property, plant, and equipment (*SPPE*). We divide our sample into three sub-samples: (i) firms for which an increase (decrease) in labor investment is accompanied by an increase (decrease) in *INVEST_ OTHER* (i.e., a positive relationship between labor and non-labor investment); (ii) firms for which an increase (decrease) in labor investment is accompanied by a decrease (increase) in *INVEST_ OTHER* or a decrease in labor investment; and (iii) firms with a missing value for *INVEST_ OTHER.* Panel E of Table 9 reports the results for the sub-samples based on the relationship between *INVEST_ OTHER* and labor investment. We find that the negative relationship between stock price informativeness and labor investment efficiency is not concentrated in the sub-sample of firms with a positive relationship between *INVEST_ OTHER* and labor investment. In fact, we also find negative and significant coefficients for $PIN_{i,t-1}$ in Models 13 to 15, further corroborating our earlier findings. Additionally, we find that the coefficient for $PIN_{i,t-1}$ is higher in the sub-sample with a positive correlation between *INVEST_ OTHER* and labor investment than in the sub-sample with a negative correlation between *INVEST_ OTHER* and labor investment, implying that stock price informativeness plays a more important role in increasing hiring when the need to increase the total of other investments is high. Collectively, our results suggest that our findings are not driven by non-labor investments.

[Insert Table 9 about here]

4.8 Other robustness tests

In this section, we describe additional tests conducted to ensure the robustness of our findings. The results of these tests, reported in Table 10, generally confirm the core findings presented in Table 3**:** more informative stock prices are associated with more efficient labor investment.

Additional control variables. We introduce additional control variables to ensure the robustness of our findings. First, we control for earnings quality ($AQ_{i,t-1}$). Earnings management may also affect labor investment efficiency (Jung et al., 2014), consistent with the conjecture that higher earnings quality mitigates the agency problems between managers and suppliers of financing, hence reduces labor adjustment costs, which leads to more efficient investment in labor. In line with Gul, Srinidhi, and Ng (2011), we use the absolute value of Dechow and Dichev's (2002) measure of abnormal accruals, as modified by Ball and Shivakumar (2005) (*AQ)*, as a proxy for earnings management. The results reported in Model 1 of Table 10 show that the coefficient for $PIN_{i,t-1}$ is negative and significant at the 1% level, corroborating our earlier findings. Second, we control for earnings informativeness ($ERC_{i,t-1}$) since it also may affect labor investment efficiency (e.g., Pinnuck and Lillis (2007)). We estimate the earnings response coefficient (*ERC*) by regressing cumulative abnormal returns on unexpected earnings calculated as the difference between current net income before extraordinary items and lagged net income before extraordinary items over the lagged market value. The results reported in Model 2 of Table 10 show that the coefficient for $PIN_{i,t-1}$ is still negative and significant at the 1% level, supporting our earlier findings.

Third, we use several mispricing proxies to ensure that our findings are due to market stock price mispricing (i.e., deviations of stock price from its fundamental value) rather than to informed trading.[19] *Firstly*, we control in Model 3 of Table 10 for analyst forecast bias using the ratio of difference between one-year-ahead consensus earnings per share and realized earnings per share over the previous year's stock price (*BIAS)*. Consensus and realized earnings per share are extracted from *I/B/E/S* while stock price is extracted from *CRSP*. A higher value for *BIAS* indicates that the stock is over-evaluated while a negative value indicates that the stock is under-evaluated. A missing value for *BIAS* indicates also that analysts also disagree about the earnings per share forecasts. *Secondly*, we include in Model 4 of Table 10 the standard deviation of analysts' earnings-per-share from I/B/E/S (*VAR_ANALYST_COV)*, in line with Bakke and Whited (2010). Analysts' disagreement about forecasted earnings per share may lead to overvaluation of stock prices (e.g., Panageas, 2005; Gilchrist, Himmelberg, and Huberman, 2005), which lead managers to increase investment.[20] *Thirdly*, we control for cumulative abnormal returns (*CAR*) dummies in Model 5 of Table 10, to ensure that our findings are not driven by extreme stock performance, in line with Ferriera et al. (2011). We include: (i) a

[19] Managers may respond to market mispricing of their stock when making investment decisions (Bakke and Whited, 2010). Specifically, managers tend to invest more when their stock is overpriced (Baker and Wurgler, 2002; Baker, Stein, and Wurgler, 2003). Therefore, we expect that mispricing leads to less investment efficiency.

[20] We find that the coefficient for $VAR\_ANALYST\_COV_{i,t-1}$ is positive and significant at the 1% level, suggesting that analysts' forecast dispersion is associated with lower labor investment efficiency, consistent with the mispricing argument.

dummy variable equal to one if a firm has a *CAR* below the 20th percentile (Q1) and zero otherwise, and (ii) a dummy variable equal to one if a firm has a *CAR* above the 80th percentile (Q5) and zero otherwise.[21],[22] The results reported in Model 5 of Table 10 show that the coefficient for $PIN_{i,t-1}$ is still negative and significant at the 1% level. Collectively, these results suggest that our findings are not driven by mispricing in stock prices.

Alternative definitions of PIN. We also use alternative definitions of PIN to ensure that our findings are not affected by measurement errors in PIN, in line with Ferreira et al. (2011). First, we re-estimate our basic model for firm-year observations with $PIN_{i,t-1}$ above the 80th percentile (Q5) and below the 20th percentile (Q1) and replace $PIN_{i,t-1}$ by $PIN_{i,t-1}$ (Q5-Q1). $PIN_{i,t-1}$ (Q5-Q1) is a dummy variable equal to one if $PIN_{i,t-1}$ is higher than the 80th percentile (Q5) and zero for firm-year observations with $PIN_{i,t-1}$ below the 20th percentile (Q5). Second, we re-estimate our basic model after replacing $PIN_{i,t-1}$ by $PIN_{i,t-1}$ (dummy), a dummy variable equal to one for firm-year observations with $PIN_{i,t-1}$ higher than the sample median and zero otherwise. The results reported in Models 6 and 7 of table 10 show that the coefficient for the alternative PIN proxies (i.e., $PIN_{i,t-1}$ (Q5-Q1) and $PIN_{i,t-1}$ (dummy)) are negative and significant at the 1% level, in line with our previous findings.

*Ex*cluding financial and utility industries. Finally, we test the robustness of our findings to an alternative sample. Specifically, we re-run our basic model after excluding firms belonging to Financial or Utility industries. The results reported in Model 8 of Table 10 show that the coefficient for $PIN_{i,t-1}$ is still negative and significant at the 1% level, corroborating our earlier findings.

[Insert Table 10 about here]

5. Conclusion

In contributing to the managerial learning literature, we choose to focus on the efficiency of investment in human capital that is one of the important factors of production that determines the firm's output. Specifically, using a sample of U.S. firms over the period 1994-

[21] We calculate *CAR* over a period of 12 months starting at the beginning of the fiscal year and ending at the end of the fiscal year.

[22] We find that the coefficients for *CAR* (below Q1 dummy) and *CAR* (above Q5 dummy) are positive and significant at the 1% level, suggesting that extreme stock performance is associated with less efficient investment in labor.

2010, we show that a higher probability of informed trading (*PIN*) (i.e., higher stock price informativeness) is associated with lower deviations of labor investment from the level justified by economic fundamentals i.e., higher labor investment efficiency. This result is consistent with the view that managers use the information incorporated in stock prices (e.g., information about future investment and growth opportunities, future relationship with stakeholders, and financing policies) when investing in human capital. This result is also consistent with the view that more informative stock prices result in a better monitoring of managers (Ferreira et al., 2011), which alleviates the empire building problem, leading to a more efficient investment in labor. Also, this result is consistent with the conjecture that stock price informativeness is associated with higher corporate transparency (e.g., Jin and Myers, 2006; Haggard et al., 2008; Hutton, 2009; Zuo, 2013) and lower cost of equity financing (e.g., Fernandes and Ferreira, 2009), which also makes it easier for firms to finance labor and hence enhances labor investment efficiency. This finding is robust to using alternative proxies for stock price informativeness and labor investment efficiency, when we control for earnings quality and mispricing, and when we address the endogeneity of PIN.

We also report evidence suggesting that stock price informativeness helps mitigate over-investment (over-hiring and under-firing) and under-investment (under-hiring and over-firing) problems in labor. Furthermore, we show that stock price informativeness plays a more (less) important role in enhancing the ability of firms to finance labor when labor unions are strong and financial constraints are high (in firms belonging to industries heavily relying on skilled labor). Additionally, we find that our findings are not affected by other investments such as capital expenditures, R&D expenses, advertising expenses, and acquisition expenses. Finally, we report evidence suggesting that stock price informativeness helps mitigate distortions in labor investment created by labor union as well as labor investment inefficiencies for firms that are more financially constrained. While the present paper highlights the importance of information incorporated into stock prices for the investment in human capital, future research can add further to the understanding of the role of stock price informativeness in determining corporate decisions by investigating whether it guides other corporate decisions, such as liquidity management and advertising.

Appendix

Variable	Description	Source
Panel A: Variables used in the main analysis		
|ABN(LABOR_INVEST)|	The absolute value of the difference between the observed value for labor investment (i.e., the difference between the current and the previous number of employees) and the predicted value of labor investment based on economic fundamentals using Model (2).	Authors' calculation
PIN	Probability of Information trading (PIN) derived from Easely, Kiefer, and O Hara (1996)'s market microstructure model.	Brown et al.'s (2004) continuously updated database
SIZE	The natural logarithm of the firm's market value.	Authors' calculation
LEV	The ratio of long-term debt over total assets.	Authors' calculation
MB	The market-to-book ratio.	Authors' calculation
NET_PPE	The ratio of the current year value of net property, plant, and equipment over the previous year value of total assets.	Authors' calculation
QUICK_RATIO	The ratio of the sum of cash and short-term investments and receivables over current liabilities.	Authors' calculation
LOSS	A dummy variable equal to one (1) if the ratio of net income over total assets (ROA) is positive, and zero (0) otherwise.	Authors' calculation
DIV_PAYER	A dummy variable equal to one (1) if the firm pays dividends, and zero (0) otherwise.	Authors' estimation
CFO_VOL	The volatility of Cash flow from operations calculated over a period of five years.	Authors' calculation
SALES_VOL	The volatility of sales and revenue calculated over a period of five years.	Authors' calculation
LABOR_INVEST_VOL	The volatility of labor investment calculated over a period of five years.	Authors' calculation
|ABN(OTHER_INVEST)|	The absolute value of the residuals from the regression of non-labor investment (i.e., the sum of capital expenditures (*CAPX*), acquisition (*AQC*), and R&D expenses (*XRD*) less proceeds from the sale of property, plant, and equipment (*SPPE*)) on sales growth.	Authors' calculation
UNION	The industry unionization rate.	Authors' calculation
LABOR_INTENSITY	The ratio of the number of employees over total assets.	Authors' calculation
IO	The fraction of the firm's shares held by institutional investors.	Authors' calculation
ACOV	The natural logarithm of one plus the number of analysts following a firm.	I/B/E/S
TURNOVER	The ratio of the number of shares traded over the number of shares outstanding.	Authors' calculation

ILLIQ	Amihud's (2002) illiquidity ratio is defined as the annual average of the ratio of the daily absolute stock return over the daily transaction volume.	Authors' calculation
SPI1	Annual firm-specific return variation proxy (log(R2/(1-R2)) estimated from regressing the firm's weekly excess return on the weekly value-weighted excess market return, the weekly small-minus-big size factor return, and the weekly high-minus-low book-to-market factor return.	Authors' calculation
SPI2	Annual firm-specific return variation proxy (log(R2/(1-R2)) estimated from regressing the firm's weekly returns on current and lagged market returns as well as current and lagged industry returns.	Authors' calculation
SPI3	Annual firm-specific return variation proxy (log(R2/(1-R2)) estimated from regressing the firm's weekly stock returns on the current week, previous week, two weeks back, one weak ahead and two weeks ahead value-weighted market returns.	Authors' calculation
EF	The external financing dependence calculated as the industry-median value of the difference between capital expenditures and cash flow from operations scaled by capital expenditures, in line with Foucault and Frésard (2012).	Authors' calculation
HIGH_SKILLED	A dummy variable equal to one for firms that belong to industries relyig more on skilled-labor, and zero otherwise. We use the industry average number of employees working in occupations with a JobZones index equal to 4 or 5 as a proxy for the degree of reliance on skilled-labor, in line with Ochoa (2013), Belo and Lin (2014), and Ghaly, Dang, and Konstantinos (2015). We collect JobZones data from Occupational Information Network (O*Net), available at http://www.onetonline.org/find/zone. We gather the data on the number of employees by occupation from Occupational Employment Statistics (OES) program of the Bureau of Labor Statistics.	Authors' calculation
Panel B: Variables used in the robustness tests		
LABOR_COST	Staff expense from Compustat, which represents wages and other benefits paid to employees and officers.	Compustat North America
REV	The firm's total revenue.	Compustat North America
DECR	A dummy variable equal to one if total revenue decreased from the previous year, and zero otherwise.	Authors' calculation
AI	The ratio of total assets over total revenue.	Authors' calculation
SUCC_DECR	A dummy variable equal to one if the firm had a decrease in revenue during the current and the previous year, and zero otherwise.	Authors' calculation
XAD	The firm's advertising expenses.	Compustat North America
PIN (Q5-Q1)	A dummy variable equal to one if *PIN* is higher than the 80th percentile (Q5), and zero for firm-year observations with *PIN* below the 20th percentile (Q5)	Authors' calculation
PIN (dummy)	A dummy variable equal to one for firm-year observations with *PIN* higher than the sample median and zero otherwise.	Authors' calculation
AQ	The absolute value of Dechow and Dichev's (2002) measure of	Authors'

	abnormal accruals, as modified by Ball and Shivakumar (2005).	calculation
ERC	The earnings response coefficient (*ERC*) calculated by regressing cumulative abnormal returns on unexpected earnings calculated as the difference between current net income before extraordinary items and lagged net income before extraordinary items over the lagged market value.	Authors' calculation
BIAS	Analyst forecast bias calculated as the ratio of difference between one-year-ahead consensus earnings per share and realized earnings per share over the previous year's stock price.	I/B/E/S & CRSP
VAR_ANALYST_COV	The standard deviation of one year-ahead analysts forecasts over mean one year-ahead analyst forecasts of earnings per share from I/B/E/S.	Authors' calculation
CAR (below Q1 dummy)	A dummy variable equal to one if a firm has 12 months cumulative abnormal returns (*CAR)* below the 20th percentile (Q1), and zero otherwise.	Authors' calculation
CAR (above Q3 dummy)	A dummy variable equal to one if a firm has 12 months CAR above the 80th percentile (Q5), and zero otherwise.	Authors' calculation

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TABLE 1

Descriptive Statistics

Variable	N	Mean	Median	Standard deviation	Q1	Q3
$\lvert$ABN(LABOR_INVEST $_{i,t}$)$\rvert$	21,551	0.152	0.099	0.156	0.045	0.202
$PIN_{i,t-1}$	21,551	0.189	0.170	0.099	0.117	0.244
$SIZE_{i,t-1}$	21,551	6.082	5.993	2.101	4.580	7.506
$LEV_{i,t-1}$	21,551	0.200	0.183	0.174	0.033	0.319
$MB_{i,t-1}$	21,551	2.673	2.043	2.143	1.325	3.282
$NET\_PPE_{i,t-1}$	21,551	0.284	0.233	0.208	0.121	0.400
$QUICK\_RATIO_{i,t-1}$	21,551	1.842	1.217	2.394	0.781	2.023
$LOSS_{i,t-1}$	21,551	0.213	0.000	0.410	0.000	0.000
$DIV\_PAYER_{i,t-1}$	21,551	0.471	0.000	0.499	0.000	1.000
$CF\_VOL_{i,t-1}$	21,551	0.075	0.051	0.491	0.030	0.086
$SALES\_VOL_{i,t-1}$	21,551	0.243	0.187	0.216	0.109	0.308
$LABOR\_INVEST\_VOL_{i,t-1}$	21,551	0.192	0.126	0.229	0.069	0.226
$\lvert ABN(OTHER\_INVEST_{i,t})\rvert$	21,551	0.105	0.093	0.109	0.052	0.130
$UNION_{i,t-1}$	21,551	10.785	7.800	10.223	2.900	14.900
$LABOR\_INTENSITY_{i,t-1}$	21,551	0.009	0.005	0.017	0.003	0.010
$IO_{i,t-1}$	21,551	0.510	0.535	0.275	0.281	0.740

This table presents descriptive statistics for the variables used in our multivariate regression analysis to examine the impact of stock price informativeness on labor investment efficiency for a sample of 21,551 firm-year observations for the 1994-2010 period. Descriptions and sources of these variables are provided in the Appendix.

Table 2

Pearson Correlation Coefficients

Variable	$\lvert ABN(LABOR\_INVEST_{i,t})\rvert$	$PIN_{i,t-1}$	$SIZE_{i,t-1}$	$LEV_{i,t-1}$	$MB_{i,t-1}$	$NET\_PPE_{i,t-1}$	$QUICK\_RATIO_{i,t-1}$	$LOSS_{i,t-1}$	$DIV\_PAYER_{i,t-1}$	$CF\_VOL_{i,t-1}$	$SALES\_VOL_{i,t-1}$	$LABOR\_INVEST\_VOL_{i,t-1}$	$\lvert ABN(OTHER\_INVEST_{i,t})\rvert$	$UNION_{i,t-1}$	$LABOR\_INTENSITY_{i,t-1}$
$PIN_{i,t-1}$	**-0.028**														
$SIZE_{i,t-1}$	**-0.129**	**-0.595**													
$LEV_{i,t-1}$	-0.001	0.006	**0.057**												
$MB_{i,t-1}$	**0.044**	**-0.255**	**0.327**	**-0.088**											
$NET\_PPE_{i,t-1}$	-0.046	0.003	**0.121**	**0.343**	**-0.116**										
$QUICK\_RATIO_{i,t-1}$	**0.082**	-0.013	**-0.100**	**-0.308**	**0.078**	**-0.250**									
$LOSS_{i,t-1}$	**0.144**	**0.086**	**-0.274**	**0.053**	**-0.053**	**-0.093**	**0.104**								
$DIV\_PAYER_{i,t-1}$	**-0.163**	**-0.121**	**0.407**	**0.094**	-0.001	**0.250**	**-0.180**	**-0.276**							
$CF\_VOL_{i,t-1}$	**0.021**	0.014	**-0.050**	**-0.038**	**0.074**	**-0.046**	**0.034**	**0.047**	**-0.057**						
$SALES\_VOL_{i,t-1}$	**0.122**	**-0.071**	**-0.069**	**-0.060**	**0.195**	**-0.117**	**0.242**	**0.169**	**-0.276**	**0.073**					
$LABOR\_INVEST\_VOL_{i,t-1}$	**0.131**	**0.034**	**-0.143**	**0.038**	0.012	**-0.114**	**0.047**	**0.128**	**-0.241**	**0.041**	**0.387**				
$\lvert ABN(OTHER\_INVEST_{i,t})\rvert$	**0.166**	**0.021**	**-0.084**	**0.018**	**0.068**	**-0.043**	**0.043**	**0.071**	**-0.072**	0.013	**0.118**	**0.051**			
$UNION_{i,t-1}$	**-0.057**	**0.022**	**0.085**	**0.220**	**-0.136**	**0.368**	**-0.130**	**-0.087**	**0.241**	**-0.034**	**-0.127**	**-0.073**	**-0.042**		
$LABOR\_INTENSITY_{i,t-1}$	0.004	**0.109**	**-0.128**	**-0.067**	-0.005	0.005	**-0.070**	**-0.052**	**-0.040**	-0.001	**-0.047**	0.007	0.008	**-0.108**	
$IO_{i,t-1}$	**-0.096**	**-0.509**	**0.613**	0.005	**0.070**	**-0.041**	**-0.040**	**-0.140**	**0.170**	**-0.045**	**-0.084**	**-0.104**	**-0.048**	**-0.036**	**-0.077**

This table presents Pearson pairwise correlation coefficients between the regression variables. The full sample includes 21,551 firm-year observations for the 1994-2010 period. Bold face indicates statistical significance at the 1% level. Descriptions and data sources for these variables are provided in the Appendix.

TABLE 3
Stock price informativeness and labor investment efficiency

Variable	Basic Model	Firm fixed effects	2SLS First stage	2SLS Second stage	Dynamic GMM	Fama-MacBeth	Median Regression
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$PINi_{,t-1}$	-0.209	-0.202		-0.284	-0.215	-0.176	-0.144
	(-14.856)***	(-11.748)***		(-3.135)***	(-3.172)***	(-6.716)***	(-12.863)***
$SIZE_{i,t-1}$	-0.008	-0.027	-0.017	-0.009	-0.014	-0.008	-0.005
	(-5.615)***	(-5.282)***	(-14.712)***	(-3.292)***	(-3.743)***	(-7.312)***	(-7.844)***
$LEV_{i,t-1}$	0.014	0.007	0.007	0.012	0.043	0.014	0.013
	(1.249)	(0.330)	(1.390)*	(0.944)	(1.217)	(2.804)***	(2.402)***
$MB_{i,t-1}$	0.003	0.005	-0.001	0.003	0.004	0.003	0.002
	(3.390)***	(2.953)***	(-3.192)***	(2.987)***	(1.523)*	(4.781)***	(4.968)***
$NET\_PPE_{i,t-1}$	0.014	0.022	0.007	0.016	-0.013	0.014	-0.023
	(1.237)	(0.798)	(1.571)*	(1.245)	(-0.360)	(1.892)**	(-4.887)***
$QUICK\_RATIO_{i,t-1}$	0.003	0.001	-0.001	0.002	0.003	0.003	0.002
	(3.265)***	(1.418)*	(-2.672)***	(2.443)***	(1.360)	(4.689)***	(5.505)***
$LOSS_{i,t-1}$	0.029	0.008	-0.011	0.029	0.019	0.029	0.025
	(8.245)***	(2.179)**	(-7.274)***	(6.996)***	(1.454)*	(6.235)***	(11.086)***
$DIV\_PAYER_{i,t-1}$	-0.022	0.003	0.004	-0.023	-0.010	-0.021	-0.016
	(-5.642)***	(0.601)	(2.235)**	(-5.066)***	(-0.756)	(-5.950)***	(-7.859)***
$CF\_VOL_{i,t-1}$	0.000	-0.005	0.000	0.000	-0.080	0.045	-0.001
	(0.527)	(-7.323)***	(0.561)	(0.513)	(-0.939)	(2.727)***	(-2.042)**
$SALES\_VOL_{i,t-1}$	0.005	0.010	-0.019	-0.001	0.034	-0.005	-0.003
	(0.564)	(1.059)	(-5.426)***	(-0.141)	(1.617)*	(-0.791)	(-0.618)
$LABOR\_INVEST\_VOL_{i,t-1}$	0.052	-0.027	0.004	0.058	-0.036	0.051	0.036
	(6.664)***	(-2.753)***	(1.299)*	(6.421)***	(-1.809)*	(9.448)***	(8.728)***
$\|ABN(OTHER\_INVEST_{i,t})\|$	0.197	0.221	-0.009	0.204	0.226	0.199	0.181
	(11.664)***	(6.161)***	(-2.108)**	(11.462)***	(4.029)***	(12.096)***	(22.826)***

UNIONi,t-1	0.000	-0.001	0.000	0.000	0.000	0.000	-0.001
	(0.893)	(-2.209)**	(0.035)	(0.037)	(0.118)	(0.193)	(-7.540)***
LABOR_INTENSITY$_{i,t-1}$	0.038	-0.971	0.142	0.054	-0.142	0.122	0.062
	(0.477)	(-2.739)***	(2.495)**	(0.682)	(-0.687)	(1.734)	(1.181)
IO$_{i,t-1}$	-0.034	-0.002	-0.062	-0.045	0.014	-0.024	-0.040
	(-3.682)***	(-0.144)	(-17.445)***	(-3.974)***	(0.608)	(-3.039)***	(-9.449)***
ACOV$_{i,t-1}$			-0.019				
			(-8.761)***				
TURNOVER$_{i,t-1}$			-0.009				
			(-10.192)***				
Intercept	0.212	0.258***	0.368	0.235	0.224	0.197	0.166
	(22.334)***	(0.031)	(82.467)***	(6.745)***	5.719	(11.695)***	(28.989)***
INDUSTRY EFFECTS	YES	YES	YES	YES	YES	YES	YES
YEAR EFFECTS	YES	YES	YES	YES	YES	YES	YES
R^2	0.085	0.508	0.472	0.074		0.102	
N	21,551	21,551	17,962	17,962	21,486	21,551	21,551

This table presents regression results of the impact of stock price informativeness on labor investment efficiency. The full sample includes 21,551 firm-year observations for the 1994-2010 period. Bold face indicates statistical significance at the 1% level. Descriptions and data sources for the regression variables are provided in the Appendix. z-statistics based on robust standard errors adjusted for clustering by firm are shown below each estimate – in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively, one-tailed when directional predictions are made, and two-tailed otherwise.

TABLE 4

Alternative proxies for stock price informativeness

Variable	Illiquidity proxy	Firm-Specific return variation proxies		
	(1)	(2)	(3)	(4)
$ILLIQ_{i,t-1}$	-0.002			
	(-7.615)***			
$SPI1_{i,t-1}$		-0.007		
		(-7.361)***		
$SPI2_{i,t-1}$			-0.009	
			(-8.463)***	
$SPI3_{i,t-1}$				-0.008
				(-6.604)***
$SIZE_{i,t-1}$	-0.006	-0.005	-0.006	-0.008
	(-4.736)***	(-4.068)***	(-4.564)***	(-5.259)***
$LEV_{i,t-1}$	0.036	0.035	0.031	0.040
	(3.167)***	(3.776)***	(2.555)***	(2.865)***
$MB_{i,t-1}$	-0.001	-0.001	-0.001	0.000
	(-1.060)	(-0.723)	(-0.892)	(0.189)
$NET\_PPE_{i,t-1}$	0.000	0.007	0.010	0.022
	(0.004)	(0.775)	(0.914)	(1.590)
$QUICK\_RATIO_{i,t-1}$	0.004	0.005	0.005	0.005
	(4.276)***	(6.477)***	(7.095)***	(6.765)***
$LOSS_{i,t-1}$	0.027	0.031	0.025	0.027
	(8.618)***	(9.564)***	(7.080)***	(6.551)***
$DIV\_PAYER_{i,t-1}$	-0.020	-0.021	-0.023	-0.024
	(-5.727)***	(-6.055)***	(-5.612)***	(-5.268)***
$CF\_VOL_{i,t-1}$	0.067	0.036	0.000	-0.001
	(2.454)**	(1.563)*	(0.363)	(-0.784)
$SALES\_VOL_{i,t-1}$	0.005	0.010	0.015	0.014

	(0.673)	(1.091)	(1.621)*	(1.257)
$LABOR\_INVEST\_VOL_{i,t-1}$	0.042	0.042	0.046	0.058
	(5.731)***	(5.559)***	(5.497)***	(5.910)***
$\vert ABN(OTHER\_INVEST_{i,t})\vert$	0.210	0.157	0.256	0.317
	(11.854)***	(8.532)***	(11.753)***	(12.645)***
UNIONi,t-1	0.000	0.000	0.000	0.000
	(0.411)	(0.440)	(1.027)	(1.266)
$LABOR\_INTENSITY_{i,t-1}$	0.089	0.055	0.347	0.200
	(0.547)	(1.470)	(1.431)	(1.481)
$IO_{i,t-1}$	-0.034	-0.032	-0.034	-0.034
	(-4.451)***	(-4.137)***	(-3.859)***	(-3.554)***
Intercept	0.167	0.171	0.179	0.178
	(21.174)***	(22.740)***	(19.930)***	(20.113)***
INDUSTRY EFFECTS	YES	YES	YES	YES
YEAR EFFECTS	YES	YES	YES	YES
R^2	0.084	0.085	0.089	0.102
N	23,157	22,348	22,619	22,542

This table presents results using alternative stock price informativeness proxies. The sample period is 1994-2010 period. Bold face indicates statistical significance at the 1% level. Descriptions and data sources for the regression variables are provided in the Appendix. z-statistics based on robust standard errors adjusted for clustering by firm are shown below each estimate – in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively, one-tailed when directional predictions are made, and two-tailed otherwise.

TABLE 5
The role of labor union and financial constraints

Variable	(1)	(2)
$PIN_{i,t-1}$	-0.177	-0.231
	(-9.103)***	(-15.731)***
$PIN_{i,t-1}$*$UNION_{i,t-1}$	-0.003	
	(-2.176)**	
$PIN_{i,t-1}$*$EF_{i,t-1}$		-0.003
		(-2.853)***
$SIZE_{i,t-1}$	-0.177	-0.009
	(-9.103)***	(-6.045)***
$LEV_{i,t-1}$	0.014	0.018
	(1.245)	(1.568)*
$MB_{i,t-1}$	0.003	0.003
	(3.446)***	(3.000)***
$NET\_PPE_{i,t-1}$	0.014	0.022
	(1.210)	(1.810)*
$QUICK\_RATIO_{i,t-1}$	0.003	0.002
	(3.281)***	(2.986)***
$LOSS_{i,t-1}$	0.029	0.028
	(8.227)***	(7.925)***
$DIV\_PAYER_{i,t-1}$	-0.022	-0.019
	(-5.691)***	(-4.936)***
$CF\_VOL_{i,t-1}$	-0.001	0.000
	(-0.571)	(0.377)
$SALES\_VOL_{i,t-1}$	0.005	0.003
	(0.589)	(0.365)
$LABOR\_INVEST\_VOL_{i,t-1}$	0.052	0.052
	(6.632)***	(6.583)***
$\lvert ABN(OTHER\_INVEST_{i,t})\rvert$	0.197	0.203

	(11.657)***	(11.972)***
$UNION_{i,t-1}$	0.000	0.000
	(1.065)	(0.329)
$LABOR\_INTENSITY_{i,t-1}$	0.036	0.011
	(0.456)	(0.136)
$IO_{i,t-1}$	-0.033	-0.030
	(-3.600)***	(-3.318)***
$EF_{i,t-1}$		0.002
		(6.320)***
Intercept	0.206	0.218
	(19.931)***	(22.920)***
INDUSTRY EFFECTS	YES	YES
YEAR EFFECTS	YES	YES
R^2	0.085	0.089
N	21,551	21,228

This table presents results for the impact of labor union and financial constraints on the relationship between stock price informativeness and labor investment efficiency. The full sample includes 21,551 firm-year observations for the 1994-2010 period. Bold face indicates statistical significance at the 1% level. Descriptions and data sources for the regression variables are provided in the Appendix. z-statistics based on robust standard errors adjusted for clustering by firm are shown below each estimate – in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively, one-tailed when directional predictions are made, and two-tailed otherwise.

TABLE 6
Over-investment versus under-investment

Variable	Panel A: Over-investment			Panel B: Under-investment		
	Total	Over-hiring	Under-firing	Total	Under-hiring	Over-firing
	(1)	(2)	(3)	(4)	(5)	(6)
$PIN_{i,t-1}$	-0.137	-0.145	-0.102	-0.224	-0.229	-0.175
	(-6.417)***	(-6.235)***	(-2.164)**	(-13.062)***	(-13.180)***	(-3.639)***
$SIZE_{i,t-1}$	-0.005	-0.005	-0.001	-0.008	-0.007	-0.006
	(-2.814)***	(-2.736)***	(-0.371)	(-4.287)***	(-4.036)***	(-1.378)*
$LEV_{i,t-1}$	0.002	0.016	-0.069	0.019	0.025	-0.004
	(0.165)	(1.186)	(-2.880)***	(1.273)	(1.592)*	(-0.192)
$MB_{i,t-1}$	0.006	0.006	0.005	0.001	0.001	0.000
	(5.341)***	(5.246)***	(1.767)**	(0.928)	(0.592)	(0.191)
$NET\_PPE_{i,t-1}$	-0.049	-0.049	-0.020	0.034	0.037	-0.080
	(-4.545)***	(-4.089)***	(-1.028)	(2.332)**	(2.431)**	(-3.831)***
$QUICK\_RATIO_{i,t-1}$	0.003	0.003	0.010	0.003	0.003	-0.008
	(2.332)**	(2.303)**	(2.755)***	(2.668)***	(2.559)**	(1.939)**
$LOSS_{i,t-1}$	-0.014	-0.022	0.008	0.047	0.054	0.029
	(2.844)***	(3.355)***	-0.974	(10.553)***	(11.513)***	(2.996)***
$DIV\_PAYER_{i,t-1}$	-0.018	-0.016	-0.022	-0.021	-0.020	-0.009
	(-4.056)***	(-3.314)***	(-2.722)***	(-4.214)***	(-3.774)***	(-1.032)
$CF\_VOL_{i,t-1}$	-0.001	-0.001	0.016	0.050	0.051	-0.067
	(-2.855)***	(-2.478)**	(0.187)	(1.517)*	(1.545)*	(-0.743)
$SALES\_VOL_{i,t-1}$	0.042	0.038	0.110	-0.008	-0.011	0.037
	(3.431)***	(2.886)***	(3.713)***	(-0.653)	(-0.944)	(1.224)
$LABOR\_INVEST\_VOL_{i,t-1}$	0.043	0.042	0.049	0.055	0.056	-0.021
	(3.693)***	(3.346)***	(2.190)**	(5.683)***	(5.634)***	(-1.103)
$\|ABN(OTHER\_INVEST_{i,t})\|$	0.282	0.289	0.112	0.050	0.054	0.098
	(13.456)***	(13.361)***	(1.425)*	(2.259)**	(2.376)**	(1.552)*
UNIONi,t-1	0.000	0.000	0.000	0.000	0.000	0.000

	(1.897)*	(1.745)*	(0.756)	(0.858)	(0.119)	(0.733)
$LABOR\_INTENSITY_{i,t-1}$	0.973	0.899	3.343	-0.102	-0.106	-1.987
	(3.764)***	(3.528)***	(5.153)***	(-1.363)	(-1.415)	(-1.901)**
$IO_{i,t-1}$	-0.003	-0.007	0.019	-0.044	-0.041	-0.040
	(-0.308)	(-0.615)	(1.063)	(-3.554)***	(-3.223)***	(-1.998)**
Intercept	0.122	0.126	0.060	0.237	0.233	0.213
	(8.192)***	(8.075)***	(1.705)*	(19.767)***	(19.302)***	(4.610)***
INDUSTRY EFFECTS	YES	YES	YES	YES	YES	YES
YEAR EFFECTS	YES	YES	YES	YES	YES	YES
R^2	0.157	0.158	0.144	0.082	0.084	0.107
N	7,171	6,005	1,166	14,380	13,775	605

This table presents the results for the over-investment and under-investment sub-samples. The results for the over-investment sub-sample are reported in **Panel A**. Model 1 reports the results for the total over-investment sub-sample (i.e., all sample firms for which the observed labor investment is higher than expected). Model 2 reports the results for the over-investment sub-sample of firms for which the expected level of labor investment is positive (over-hiring). Model 3 reports the results for the over-investment sub-sample of firms for which the expected level of labor investment negative (under-firing). The results for the under-investment sub-sample are reported in **Panel B**. Model 4 reports the results for the total under-investment sub-sample (i.e., all sample firms for which the observed labor investment is lower than expected). Model 5 reports the results for the under-investment sub-sample of firms for which the expected level of labor investment is positive (under-hiring). Model 6 reports the results for the over-investment sub-sample of firms for which the expected level of labor investment negative (over-firing). The full sample includes 21,551 firm-year observations for the 1994-2010 period. Bold face indicates statistical significance at the 1% level. Descriptions and data sources for the regression variables are provided in the Appendix. z-statistics based on robust standard errors adjusted for clustering by firm are shown below each estimate – in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively, one-tailed when directional predictions are made, and two-tailed otherwise.

TABLE 7

High- versus low- skilled labor

Variable	**Panel A:** Total Sample		**Panel B:** Over-investment		**Panel B:** Under-investment	
	High-skilled	Low-skilled	High-skilled	Low-skilled	High-skilled	Low-skilled
	(1)	(2)	(3)	(4)	(5)	(6)
$PIN_{i,t-1}$	-0.199***	-0.206***	-0.086**	-0.183***	-0.234***	-0.198***
	(-7.555)	(-13.241)	(-2.272)	(-7.118)	(-8.210)	(-10.355)
$SIZE_{i,t-1}$	-0.011***	-0.007***	-0.007***	-0.001	-0.010***	-0.007***
	(-4.722)	(-4.409)	(-2.954)	(-0.447)	(-3.758)	(-3.607)
$LEV_{i,t-1}$	0.021	0.010	0.000	-0.002	0.024	0.020
	(1.232)	(0.815)	(0.007)	(-0.087)	(1.208)	(1.165)
$MB_{i,t-1}$	0.003**	0.003***	0.007***	0.004***	0.002	0.001
	(2.429)	(3.228)	(4.789)	(2.608)	(0.849)	(0.698)
$NET\_PPE_{i,t-1}$	0.044**	-0.005	-0.027*	-0.068***	0.075***	0.002
	(2.359)	(-0.417)	(-1.946)	(-4.343)	(3.340)	(0.136)
$QUICK\_RATIO_{i,t-1}$	0.003***	0.002*	0.004**	0.002	0.003**	0.002*
	(2.924)	(1.778)	(2.341)	(0.890)	(2.362)	(1.848)
$LOSS_{i,t-1}$	0.028***	0.026***	-0.012*	-0.012	0.039***	0.051***
	(5.809)	(5.508)	(-1.915)	(-1.587)	(6.760)	(8.350)
$DIV\_PAYER_{i,t-1}$	-0.023***	-0.017***	-0.014**	-0.026***	-0.026***	-0.008
	(-4.181)	(-3.875)	(-2.560)	(-3.899)	(-3.878)	(-1.310)
$CF\_VOL_{i,t-1}$	-0.001	0.011	-0.001***	-0.000	0.101***	0.014
	(-0.935)	(0.391)	(-3.030)	(-0.004)	(2.848)	(0.373)
$SALES\_VOL_{i,t-1}$	0.002	0.009	0.035**	0.050**	-0.018	0.006
	(0.200)	(0.715)	(2.426)	(2.450)	(-1.209)	(0.334)
$LABOR\_INVEST\_VOL_{i,t-1}$	0.042***	0.059***	0.053***	0.037**	0.049***	0.059***
	(4.123)	(5.321)	(3.332)	(2.236)	(3.917)	(4.218)
$\lvert ABN(OTHER\_INVEST_{i,t})\rvert$	0.214***	0.185***	0.324***	0.241***	0.044	0.057*
	(8.360)	(8.612)	(12.185)	(8.087)	(1.526)	(1.660)
UNIONi,t-1	0.000	-0.000	0.000	0.000	-0.000	-0.000
	(0.266)	(-0.905)	(1.308)	(1.388)	(-0.100)	(-0.361)

LABOR_INTENSITY$_{i,t-1}$	0.012	0.044	0.632**	1.520***	-0.072	-0.197**
	(0.120)	(0.529)	(2.272)	(4.656)	(-0.698)	(-2.082)
IO$_{i,t-1}$	-0.036***	-0.037***	0.004	-0.000	-0.045***	-0.060***
	(-2.696)	(-3.867)	(0.346)	(-0.008)	(-2.763)	(-4.751)
Intercept	0.226***	0.198***	0.103***	0.128***	0.253***	0.219***
	(14.855)	(17.412)	(4.774)	(6.267)	(14.570)	(15.457)
INDUSTRY EFFECTS	YES	YES	YES	YES	YES	YES
YEAR EFFECTS	YES	YES	YES	YES	YES	YES
R^2	0.079	0.092	0.187	0.141	0.077	0.098
N	10,782	10,769	3,588	3,583	8,192	6,188

This table presents the results for the High-skilled (i.e., all sample firms belonging to industries that rely more on high-skilled labor) and Low-skilled (i.e., all sample firms belonging to industries that rely less on high-skilled labor) sub-samples. The results for the full sample are reported in **Panel A**. The results for the over-investment sub-sample (i.e., all sample firms for which the observed labor investment is higher than expected) are reported in **Panel B**. The results for the under-investment sub-sample (i.e., all sample firms for which the observed labor investment is lower than expected) are reported in **Panel C**. The full sample includes 21,551 firm-year observations for the 1994-2010 period. Bold face indicates statistical significance at the 1% level. Descriptions and data sources for the regression variables are provided in the Appendix. z-statistics based on robust standard errors adjusted for clustering by firm are shown below each estimate – in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively, one-tailed when directional predictions are made, and two-tailed otherwise.

TABLE 8

Alternative labor investment efficiency proxies

Variable	Alternative definitions of $\lvert ABN(LABOR\_INVEST)\rvert$				Variable	Wages and Salaries
	(1)	(2)	(3)	(4)		(5)
$PINi_{,t-1}$	-0.092***	-0.128***	-0.110***	-0.049***	$Log\ (REV_{i,t}/REV_{i,t-1})$	0.005**
	(-9.104)	(-12.639)	(-11.009)	(-6.563)		(2.345)
$SIZE_{i,t-1}$	-0.005***	-0.006***	-0.005***	-0.001***	$DECR_{i,t}*Log\ (REV_{i,t}/REV_{i,t-1})$	-0.017
	(-7.184)	(-8.348)	(-6.838)	(-2.631)		(-1.326)*
$LEV_{i,t-1}$	-0.011	-0.006	-0.012*	-0.024***	$\boldsymbol{DECR_{i,t}*Log\ (REV_{i,t}/REV_{i,t-1})*PIN_{i,t}}$	**0.144*** **
	(-1.513)	(-0.891)	(-1.842)	(-5.230)		**(2.792)**
$MB_{i,t-1}$	0.004***	0.003***	0.003***	0.001**	$DECR_{i,t}*Log\ (REV_{i,t}/REV_{i,t-1})*AI_{i,t}$	-0.001***
	(7.052)	(5.611)	(4.842)	(2.021)		(-4.055)
$NET\_PPE_{i,t-1}$	-0.027***	-0.027***	-0.027***	-0.027***	$DECR_{i,t}*Log\ (REV_{i,t}/REV_{i,t-1})*SUCC\_DECR_{i,t}$	0.007
	(-4.128)	(-5.043)	(-5.144)	(-6.759)		(0.464)
$QUICK\_RATIO_{i,t-1}$	0.001	0.001	0.002***	0.000	$DECR_{i,t}*Log\ (REV_{i,t}/REV_{i,t-1})*LOSS_{i,t-1}$	-0.036**
	(1.373)	(1.052)	(2.925)	(0.482)		(-2.048)
$LOSS_{i,t-1}$	0.011***	0.016***	0.013***	-0.007***	$PIN_{i,t}$	-0.002
	(2.588)	(6.283)	(5.170)	(-4.324)		(-1.243)
$DIV\_PAYER_{i,t-1}$	-0.016***	-0.014***	-0.014***	-0.010***	$AI_{i,t}$	0.000***
	(-4.877)	(-5.981)	(-6.250)	(-5.593)		(4.301)
$CF\_VOL_{i,t-1}$	0.002***	0.002***	0.003***	0.004***	$SUCC\_DECR_{i,t}$	-0.002
	-3.764	-3.095	-4.404	-5.289		(-1.593)
$SALES\_VOL_{i,t-1}$	0.048***	0.044***	0.039***	0.019***	$LOSS_{i,t-1}$	-0.004***
	(5.926)	(5.459)	(5.165)	(4.119)		(-2.979)
$LABOR\_INVEST\_VOL_{i,t-1}$	0.046***	0.041***	0.044***	0.006	Intercept	-0.002
	(5.899)	(6.624)	(7.374)	(1.510)		(-0.930)
$\lvert ABN(OTHER\_INVEST_{i,t})\rvert$	0.252***	0.261***	0.238***	0.086***	INDUSTRY EFFECTS	YES
	(13.991)	(14.806)	(14.304)	(7.167)	YEAR EFFECTS	YES
$UNION_{i,t-1}$	0.000	0.000	0.000	-0.000***	R^2	0.024
	(-0.522)	-0.336	-0.001	(-6.530)	N	7942

$LABOR\_INTENSITY_{i,t-1}$	0.158*	0.139*	0.115	-0.058
	(1.658)	(1.755)	(1.403)	(-1.190)
$IO_{i,t-1}$	-0.016***	-0.010**	-0.016***	-0.013***
	(-3.355)	(-2.125)	(-3.495)	(-3.829)
Intercept	0.125***	0.139***	0.133***	0.098***
	(15.089)	(20.343)	(19.513)	(20.700)
INDUSTRY EFFECTS	YES	YES	YES	YES
YEAR EFFECTS	YES	YES	YES	YES
R^2	0.077	0.118	0.111	0.058
N	21,551	21,551	21,522	21,551

This table presents our results when we use alternative labor investment efficiency problems. The full sample includes 21,551 firm-year observations for the 1994-2010 period. Boldface indicates statistical significance at the 1% level. Descriptions and data sources for the regression variables are provided in the Appendix. z-statistics based on robust standard errors adjusted for clustering by firm are shown below each estimate, in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively, one-tailed when directional predictions are made and two-tailed otherwise.

TABLE 9

The role of other investments

*The role of other investments*Variable	Panel A: *CAPX*			Panel B: *XRD*			Panel C: *XAD*		
	Positive	Negative	Zero	Positive	Negative	Zero	Positive	Negative	Zero
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$PIN_{i,t-1}$	-0.222	-0.192	-0.158	-0.208	-0.138	-0.253	-0.144	-0.16	-0.231
	(-11.978)***	(-10.497)***	(-1.732)**	(-9.090)***	(-6.873)***	(-11.164)***	(-4.476)***	(-5.899)***	(-12.990)***
Intercept and controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
INDUSTRY EFFECTS	YES	YES	YES	YES	YES	YES	YES	YES	YES
YEAR EFFECTS	YES	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.102	0.066	0.18	0.125	0.1	0.082	0.106	0.1	0.085
N	11,864	9,518	169	5,982	5,120	10,449	3,218	2,804	15,529

Variable	Panel D: *AQC*			Panel E: *OTHER_INVEST*		
	Positive	Negative	Zero	Positive	Negative	Zero
	(10)	(11)	(12)	(13)	(14)	(15)
$PIN_{i,t-1}$	-0.245	-0.156	-0.106	-0.198***	-0.164***	-0.211***
	(-13.805)***	(-5.775)***	(-3.230)***	(-8.549)	(-5.859)	(-11.562)
Intercept and controls	YES	YES	YES	YES	YES	YES
INDUSTRY EFFECTS	YES	YES	YES	YES	YES	YES
YEAR EFFECTS	YES	YES	YES	YES	YES	YES
R^2	0.127	0.064	0.083	0.146	0.094	0.070
N	6,861	3,623	11,067	5,637	1,491	14,423

This table presents the results for the impact of non-labor investment on the relationship between stock price informativeness and labor investment efficiency. The results for the sub-samples based on capital expenditure (*CAPX*) are reported in **Panel A**. The results for the sub-samples based on R&D expenses (*XRD*) are reported in **Panel B**. The results for the sub-samples based on advertising expenses (*XAD*) are reported in **Panel C**. The results for the sub-samples based on acquisitions (*AQC*) are reported in **Panel D**. The results for the sub-samples based on acquisitions (*OTHER_INVEST*) are reported in **Panel E**. Models 1, 4, 7, 10, and 13 report the results for the sub-sample of firms for which an increase (a decrease) in labor investment is accompanied with an increase (a decrease) in non-labor investment (i.e., a positive relationship between labor and non-labor investments). Models 2, 5, 8, 11 and 14 report the results for the sub-sample of firms for which an increase (a decrease) in labor investment is accompanied with a decrease (an increase) in non-labor investment (i.e., a negative relationship between labor and non-labor investments). Models 3, 6, 9, 12, and 15 report the results for the sub-sample of firms with a missing value for non-labor investment (i.e., firms without *CAPX*, *XRD*, *XAD*, *AQC*, and *OTHER_INVEST*, respectively). We only report (for the sake of space) the results for our test variable i.e., $PIN_{i,\ t-1}$. The full sample includes 21,551 firm-year observations for the 1994-2010 period. Bold face indicates statistical significance at the 1% level. Descriptions and data sources for the regression variables are provided in the Appendix. z-statistics based on robust standard errors adjusted for clustering by firm are shown below each estimate – in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively, one-tailed when directional predictions are made, and two-tailed otherwise.

TABLE 10

Additional robustness tests

Variable	Additional control variables				
	$AQ_{i,t-1}$	$ERC_{i,t-1}$	$BIAS_{i,t-1}$	$VAR\_ANALYST\_COV_{i,t-1}$	CAR
	(1)	(2)	(3)	(4)	(5)
$PIN_{i,t-1}$	-0.202	-0.209	-0.131	-0.073	-0.203
	(-13.902)***	(-14.866)***	(-6.918)***	(-3.007)***	(-14.486)***
$AQ_{i,t-1}$	0.003				
	-1.204				
$ERC_{i,t-1}$		0.000			
		(0.725)			
$BIAS_{i,t-1}$			0.003		
			(1.435)*		
$VAR\_ANALYST\_COV_{i,t-1}$				0.004	
				(1.328)*	
$CAR_{i,t-1}$ (below Q1 dummy)					0.012
					(4.588)***
$CAR_{i,t-1}$ (above Q3 dummy)					0.018
					(6.071)***
Intercept and controls	YES	YES	YES	YES	YES
INDUSTRY EFFECTS	YES	YES	YES	YES	YES
YEAR EFFECTS	YES	YES	YES	YES	YES
R^2	0.082	0.085	0.076	0.073	0.088
N	20,012	21,551	17,771	14,722	21,551

Variable	PIN Q5-Q1	PIN dummy	Excluding financial & Utility
	(6)	(7)	(8)
$PIN_{i,t-1}$			-0.220
			(-16.601)***
$PIN_{i,t-1}$ (Q5-Q1)	-0.019		
	(-3.469)***		
$PIN_{i,t-1}$ (dummy)		-0.011	
		(-3.420)***	
Intercept and controls	YES	YES	YES
INDUSTRY EFFECTS	YES	YES	YES
YEAR EFFECTS	YES	YES	YES
R^2	0.071	0.075	0.112
N	8,610	21,551	19,244

This table presents results of additional robustness tests. We only report (for the sake of space) the results for our test variable i.e., $PIN_{i,t-1}$ and the added control variables. The full sample includes 21,551 firm-year observations for the 1994-2010 period. Bold face indicates statistical significance at the 1% level. Descriptions and data sources for the regression variables are provided in the Appendix. z-statistics based on robust standard errors adjusted for clustering by firm are shown below each estimate – in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively, one-tailed when directional predictions are made, and two-tailed otherwise.