Identifying Overvalued Stocks with Corporate Job Postings*

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Abstract

Separating overvalued from just highly-valued stocks is a major objective of investment analysis, since, as Jensen (2004) stated, "overvalued stocks will, by definition, collapse." Highly-valued stocks, in contrast, can persist in their elevated valuation. We claim in this study that the rate of firms' job postings – a new metric used in investment analysis – can distinguish between overvalued and highly-valued stocks. Using a database that covers the near-universe of the online corporate job postings in the U.S., we document that the rate of firms' job postings indeed contributes to the separation of highly- from overly-valued shares, incrementally to conventional valuation measures used by investors. Of special interest is our finding that the rate of job postings strongly separated highly- from overly-valued shares during the Covid-19 period. We substantiate our findings by establishing that the rate of job postings predicts the growth of firms' sales and gross profit for at least three years, controlling for conventional growth predictors, such as R&D, capital expenditures, and the book-to-market ratio, hence the power of job postings to separate overvalued from the growth-driven highly-valued stocks.

Keywords: Job postings, Labor Demand, Valuation, Alternative data

JEL-Classification: G01, G12, G32, J23, M41

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1 Introduction

As of October 2019, the last pre-Covid year, Amazon had a price-earnings (PE) ratio of 72, whereas star performers Apple and Microsoft had lowly PE ratios of 19 and 27, respectively.[1] Amazon is undoubtedly a highly-valued stock, but is it overvalued? Overvalued stocks, by definition, are bound to fall, and some to collapse since real corporate performance cannot justify investors' unrealistically high expectations, while highly-valued stocks can persist in their elevated valuation as long as the firm's performance and prospects justify investors' high valuation. Jensen (2004) observed, "When a firm's equity becomes substantially overvalued, it sets in motion a set of organizational forces that are extremely difficult to manage – forces that almost inevitably lead to the destruction of part or all of the core value of the firm."

Naturally, differentiating between highly- and overly-valued stocks is a major objective of investors who consider whether to buy, hold, or sell securities. Investors often use crude measures, like the relative book-to-market (relative to the industry mean/median), or relative price-earnings (PE) ratios, to identify overvaluation.[2] But Amazon, with a huge relative market-to-book margin, apparently doesn't signal overvaluation to most investors since its stock price doesn't trend downward subsequent to 2019. There is, therefore, a need to improve investors' distinction between highly-valued and overvalued stocks, or the identification of overvalued shares by new, fundamental measures.

We document in this study that the rate of corporate job posting indeed distinguishes between highly-valued and overvalued stocks, indicating that job posting is, in the recent terminology, an "alternative data" (to financial information), suitable for financial analysis. The database we use for our tests covers the near-universe of online corporate job postings in the United States. It allows us to observe the complete job posting profile of each company,

[1] Data from https://finance.yahoo.com/.

[2] Some investors use for valuation purposes the PEG (price-earnings-growth) ratio, scaling the PE ratio by expected earnings growth. Interestingly, Amazon's PEG ratio is only 0.93, where overvaluation is indicated by a larger than one PEG. We note that the PE ratio is not the only information investors use. We use the PE ratio to motivate our study of using alternative new data to value firms.

thereby estimating firm-level labor demand and skill requirements. Each posting in the database provides detailed information about the employer, job title, job location, and job requirements, such as skills, certification, experience, and education level. See, an example of a job posting in Appendix B.

We start the paper with the main theme of this study: distinguishing between highly-valued and overvalued firms. We expect that job postings will contribute to the separation of highly-valued from overvalued firms because the former – highly successful enterprises – will have an above-average job posting rate (labor demand) required to support their successful performance and future growth, whereas the latter – essentially under-performing firms – are expected to have below-average job postings. To test this conjecture, we follow Fama-French (1992; 1996) and focus on the firms that are in the top 30% of the market-to-book ratio ranking. We consider this group as containing both highly-valued and overvalued stocks. We then compare the firms that remained in the 30% highly valued category throughout the examined period – which obviously were highly-valued firms – with those that dropped off the top 30% stocks, demonstrating that they were overvalued. We find that firms with high job posting rates are significantly more likely to stay in the 30% highly valued category than firms with low job posting rates, consistent with the expectation that the information contained in job postings helps separate firms that are highly valued from those that are overvalued.

Furthermore, we show that job posting rates strongly maintained their ability to separate highly- from overly-valued stocks even in the valuation challenging period of the Covid-19 crisis, which we use as an important economic downturn. We also conduct portfolio tests and find consistent results. Lastly, we show that the majority of the separation effect comes from within industry variations and that this job postings effect is robust to controlling for R&D spending, long-term analyst forecasts, and firms' earnings management.[3]

To gain insight into the reasons for the ability of job postings to separate overvalued from

[3] Jensen (2004) predicts that overvalued firms will engage in earnings management to mask the overvaluation from investors.

highly-valued firms, we test whether firms' job posting rates predict future firm performance, measured by sales growth and by gross profit growth, and document that indeed job posting rates predict significantly and incrementally to conventional financial measures the future performance of firms. Specifically, job postings predict sales growth for at least three years ahead, and the same for gross profits, incrementally to conventional growth predictors, such as R&D, Capital Investment (Capx), and the Book-to-Market ratio. For one year ahead, a one-standard-deviation increase in job posting rate is associated with a 22% rise in the sample sales growth average. A particularly economically meaningful finding. We thus obtain both statistically and economically meaningful results. In contrast, the capital expenditure and the R&D investment rates – two primary financial statement measures of investment in future growth – fail to significantly predict future sales growth, incrementally to job posting rates, at any of the horizons examined in our study. Including in the regression common control variables, such as size, the book-to-market ratio, leverage, a loss dummy, cash holding, and the contemporaneous sales growth, has little effect on the point estimates of the job posting rates. We obtain similar results for the gross profit rate as an additional key firm performance measure. At the one year ahead horizon, a one-standard-deviation increase in the job posting rate is associated with a 23% rise in the gross profit growth sample average. Overall, the ability of job posting rates to successfully predict firms' performances, underlies the success of job posting in separating overvalued from highly-valued stocks.

We next examine the heterogeneity of the predictive performance of job posting rates for firms with different characteristics. First, we classify firms into employee high- and low-skill subsamples and examine the predictive performance of job postings within each skill subgroup. We find that the predictive performance of job postings for sales growth and gross profit growth is stronger for high-skill firms. Second, we classify firms based on their employee productivity, as measured by the ratio of earnings to the number of employees, and find that the predictive-ability performance of job postings is markedly stronger for high employee productivity firms. We thus establish the higher ability of job postings to predict the performance of firms with highly-skilled and productive employees.

It should be noted that the applicability of our findings to financial statement and investment analysis extends beyond separating overvalued from highly-valued stocks. We chose here to highlight this use of job posting data for an important issue of considerable concern to investors: How to distinguish between highly-valued and overvalued stock? But firm labor data have other uses in financial and investment analysis, such as performance analysis and growth prediction, and perhaps even liquidity analysis. Our tests show that job postings qualify as an "alternative data," with incremental usefulness to conventional accounting information.

We briefly discuss the relationship of our study to related ones. We use a database that covers the near-universe of online job postings in the United States. Hershbein and Kahn (2018) use similar job posting data to show that recessions accelerate the adoption of new technologies. Liu (2018) reports that firms' abnormal job posting rates contain information about their expected returns and cash flows. Liu and Wu (2019) construct a labor-linked network based on job postings and study the transmission of economic shocks along the labor-linked network. Gutierrez et al. (2019) show that investors react positively to the disclosure of online job postings. To the best of our knowledge, this study is the first to use job posting data to separate highly-valued from overvalued stocks, and establish the reasons for the predictive ability of job postings.

This paper also relates to the literature on human capital and investment plan (e.g., Lamont, 2000; Zingales, 2000). Zingales (2000) argues that companies in today's economy are mostly human-capital-intensive, and the quest for more innovation increases the importance of human capital. At the same time, Lamont (2000) suggests that investment plans are highly informative measures of expected investment and substantial forecasting power for excess stock returns. Job postings may be thought of as a planned investment in human capital, and we show that it strongly predicts future performances and separates highly- from overly-valued firms.

Our paper also relates to a stream of literature that studies the role of nontraditional, beyond-accounting information in forecasting equity value and firm performance, such as geographical spread and penetration rates of cellar phone companies (Amir and Lev, 1996), aggregate opinion from individual tweets (Bartov et al., 2017), Google searches of firm products (Chiu et al., 2018), real-time corporate sales (Froot et al., 2017), and big data, such as consumer transactions and satellite images (Zhu, 2019).

The rest of the paper is organized as follows. Section 2 discusses the data we use. Section 3 explains our research design. Section 4 reports the stock overvaluation empirical results, while Section 5 present the firm performance prediction findings. Section 6 concludes the paper.

2 Data

2.1 Job Postings

We construct measures of firm-level job postings using data from the Burning Glass Technologies Company (BGT). Appendix B provides an example of such a job posting. BGT scans more than 40,000 online job boards and company websites to continuously collect job postings. The company parses and eliminates duplicate postings and transforms them into machine-readable form. BGT presents that its database captures nearly all online job postings and covers every Metropolitan Area in the U.S. The data are available for 2007, and from 2010 to 2017.[4] When we study the ability of job postings to differentiate highly- from overly-valued stocks during the Covid crisis, we use the last year of the sample to measure firms' job postings.

Each posting in the database provides detailed information about the employer, job title, job location, and requirements, such as skills, certification, experience, and education level. The dataset allows us to analyze an important but largely unexplored aspect of firm activities: demand for labor inputs. After matching individual job postings with employers, the BGT dataset allows firm-level analyses based on different skill levels. The richness of the BGT data comes, however, with a few shortcomings. The database covers only U.S. firms, and

[4]This is the maximum amount of data we have access to.

only covers online postings. Even though job postings have increasingly appeared online, the types of jobs posted online may not be representative of all job openings. However, Hershbein and Kahn (2018) showed that the distributions of BGT postings are relatively stable across time, and the aggregate and industry trends in the number of vacancies track non-online sources reasonably closely.

We restrict our sample to postings that include the employer's name. An important step in our study was to match the BGT database to Compustat. Since the only available firm identifier in BGT is the employer name, the matching procedure contained both machine-matching and manual-matching components. To match the BGT database to Compustat, we use a linking table from Liu (2018). In most of our tests, we aggregate job postings to the firm-year level.

Table 1 reports the industry representativeness of the sample by comparing our BGT sample with Compustat. Our sample is restricted to firms listed on major stock exchanges, including NYSE, NASDAQ, and AMEX. Overall, the BGT sample represents 65% of the Compustat population by firm counts and 83% by market capitalization. The BGT representativeness is fairly even across industries. Compared to Compustat, the most under-represented industry in our sample is Mining and Logging (43.3%), while the most over-represented industry is Retail Trade (79.5%). Overall, our BGT sample seems fairly representative of the publicly listed companies on major U.S. stock exchanges.

The focus variable of our study is the firm-year vacancy posting rate, defined as the number of new vacancy posts listed online during a year, eliminating repeated posts, and scaled by the beginning of year total asset. While it may seem more appropriate to scale job postings by the firm's number of employees, the number of employees is not a GAAP measure and is therefore missing for many firms. It is also not well defined: for example, how to count part-time employees and freelancers? Nevertheless, we replicated our tests with job postings scaled by the total number of employees and found almost identical results to those reported below. We include firm-fixed effects in some of our regression specifications to remove time-invariant firm characteristics. In additional tests, we examine the quarterly frequency of posting rates and obtain similar results to the annual tests reported below.

2.2 Main Sample

To construct our sample, we merged the firm-year job posting measures with firm financial and accounting information from Compustat. We exclude financial firms (SIC codes in the range 6000-6999) and utilities (SIC codes in the range 4900-4999) from the sample and require firms to have at least 50 employees. Variable definitions are provided in Appendix A, and all continuous variables are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers. Table 2 presents the summary statistics of the variables used in the analysis. There are 17,780 firm-year observations of firms listed on major stock exchanges with available job posting data. The mean and median job posting rates are 0.009 and 0.002, respectively. The sample firms have a median capital investment rate of 0.032, a median R&D spending rate of 0.008 (scaled by assets), a median book-to-market ratio of 0.391, a median size of $7.213 billion, a median leverage of 0.196, and a median cash holding of 0.137, relative to total assets. The mean firm reports losses infrequently (less than 20%), and the mean and median sales growth for the sample are 0.113 and 0.063, respectively. The mean and median gross profit growth rates for the sample are 0.103 and 0.067, respectively.

3 Research Design

3.1 High-Valuation vs. Overvaluation

To examine the predictive ability of job postings with respect to firm valuation, we conduct the following analysis: First, for each of the years 2007, and 2010-2016, we stop at 2016 because some of our tests use three future years. We identify the high valuation and overvalued firms as those in the top 30% of stocks ranked by the market-to-book (MB) ratio (following Fama and French, 1992), where market-to-book is measured at the end of the previous fiscal year. Next, for each year's top 30% of firms, we designate an indicator variable that equals one if the firm dropped from the top 30% group during the next two or three years. We consider these firms that were originally in the high valuation group but subsequently dropped out as *overvalued in the first year* of the examined period. Firms which remained in the top group are designated highly valued. The market-to-book ratio used to identify the stocks that dropped off is the market-to-book ratio at the end of years $t + 2$ or $t + 3$ subsequent to the initial year. We then test whether job posting rates can predict overvalued firms using the following logit and probit models. The logit model is:

$$Pr\,(fall = i) = \frac{e^{\beta_i x}}{\sum_{k=0}^{1} e^{\beta_i x}}, \tag{1}$$

where i equals 1 if the firm dropped of the highly valued group, and 0 if the firm stayed in the highly valued group throughout the examined period.

To determine the economic magnitude and robustness of the overvaluation logit and probit results, we use an alternative empirical strategy of forming portfolios. Specifically, for each year, we rank the top firms (top 30% MB) by posting rates and form decile (or quintile) portfolios of increasing posting rates. We then calculate for each portfolio the percentage of firms that dropped off the top 30% during the next two (three) years and expect the percentage of attrition to decrease with the increase in job posting rates.

3.2 Predicting Firm Performance

To gain insight into the ability of job postings to distinguish between highly-valued and overvalued firms, we examine whether firms' job posting rates contain information about future firm performance. Our model specification is the following:

$$Y_{i,t+h} = \alpha + \beta \times Posting_{i,t} + Controls_{t,t} + \lambda_t + \gamma_i + \epsilon_t, \tag{2}$$

where $Posting_{i,t}$ is the job posting rate (new posts in a given year scaled by assets) for firm i at time t, and $Y_{i,t+h}$ is the firm's performance, alternatively measured as sales growth or gross profit growth from time t to time $t + h$. We set h to 1, 2, and 3 years. We include in the regression the following controls that may affect both the posting rates and firm performance: firm size, measured as the logarithm of total assets at the beginning of the year; the book-to-market (BM) ratio, measured as the book (equity) to total market value ratio; leverage, as the sum of long-term and short-term debt scaled by the most recent total asset; a loss dummy, as an indicator for negative earnings after adding R&D back to earnings; the firm's cash holdings, as the cash and the short-term investment balances scaled by the most recent total asset; and *contemporaneous* sales growth or gross profit growth. Appendix A provides detailed variable definitions. The term λ_t is the time fixed effect which removes unobserved common year shocks, and γ_i is the firm fixed effect that removes time-invariant firm characteristics. ϵ_t is the usual error term.

3.3 Subsamples

High Skill vs. Low Skill Firms

Each year, we create an indicator variable that equals one if the firm's employee skill requirement in its job postings is above the sample median skill level, and zero otherwise. We define a firm's skill level as the ratio of job postings requiring at least a bachelor's degree, or more than five years of experience, to the total job postings of the firm in a given year. We test the baseline model (1) for high-skill and low-skill firms separately.

Employee Productivity

It stands to reason that the predictive ability of job postings will be stronger for firms with high employee productivity. Adding employees to low-productivity firms would have a minor effect on firm performance. We, therefore, test the performance predictability of job posting rates conditional on employee productivity, defined as earnings divided by the most recent number of employees. In each year, we create an indicator variable that equals one if the firm's employee productivity is above the sample median, and zero otherwise. We test the baseline model (1) for firms with high employee productivity and those with low employee productivity separately.

4 Empirical Findings: Identifying Overvalued Shares

We examine here whether firms' job postings can differentiate between highly-valued and overvalued shares. Common stocks can be overvalued by investors, sometimes for protracted periods of time (e.g., the tech bubble of the late 1990s). Many stock market anomalies were attributed to overvaluation. For example, the "value anomaly," where investing in low-valuation stocks and shorting high-valuation stocks yielded abnormal returns for decades, was explained by Lakonishok et al. (1994) as driven by the systematic overvaluation of past high growth firms and undervaluation of past losers by naïve investors.[5] Importantly, on the hazards of systematic overvaluation, see Jensen (2004).

4.1 Overall Effect

We examine the ability of job postings to differentiate between overvalued and highly-valued stocks by predicting the likelihood of firms dropping off the highly valued category (top 30% MB), using the job posting rates. Specifically, for each year, we determine a sample of top valuation firms as those in the top 30% ranking of stocks by the market-to-book ratio, following Fama and French (1992). The market-to-book ratio is measured at the end of the previous fiscal year. Next, within these top valuation firms each year, we define an indicator variable that equals one if the firm drops from the top 30% during the next two or three years. We denote these firms as *overvalued* in the first year. We then examine whether firms' job posting rates predict overvalued firms using the logit and probit models. Table 3 presents the results. Panel A of 3 is based on the logit model, and Panel B is based on the probit model.

Based on the logit model, Table 3, Panel A, Columns (1) and (2), job posting rates are negatively and significantly associated with the stocks which dropped off the top valuation category at both the two-year and three-year horizons. Stated differently, firms with low job posting rates are more likely to drop off the highly valued category of stocks. Columns

[5] Value investment lost its edge in the past 12 years. For explanation, see Lev and Srivastava (2019).

(3) and (4) of Panel A include the conventional growth predictors, Capex, and R&D. The job posting coefficients decrease somewhat but are still significant. Columns (5) and (6) add all the control variables. The job posting coefficients are still negative and significant, although at a lower level. Most of the control variables behave as expected: overvalued firms are smaller, have higher book-to-market ratios, higher leverage, less cash, and lower R&D intensity than highly-valued firms. The positive coefficient of Capex is surprising.

The two right columns of Panel A of Table 3 report the marginal effects of the explanatory variables on the probability of dropping off the high-valuation category by the coefficients from the logit model estimations, when these variables increase by one. Notably, the marginal effect of job postings is the second largest of all variables, after the loss dummy.

Moving to the probit model (Panel B), job posting rates are also found to be negatively and significantly associated with falling off the top valuation category, at both the two-year and three-year horizons. Columns (3) and (4) include job posting rates, capital investment, and R&D investment rates as the independent variables. The magnitudes of the job posting point estimates are similar to those in the standalone regressions. In columns (5) and (6), we include all the control variables. The coefficient estimates on the job posting rates are still negative and statistically significant at least at the 5% level. The coefficients of the control variables are similar to those of the logit analysis. Panel B of Table 3 also reports in the right columns the marginal effects of the explanatory variables on the probability of dropping out by the coefficients from the probit model estimations when these variables increase by one. Once more, the job postings' marginal effects are the second highest. We thus conclude that firms' job postings contribute statistically and incrementally to conventional performance predictors for the identification of *overvalued shares.*

4.1.1 The Covid-19 Period

In this subsection, we further examine the ability of job posting rates to separate highly- from overly-valued assets during severe economic downturns. We use the onset of Covid-19 at the end of the first quarter of 2020 as a period of such economic downturn, when the stock market plummeted. The pandemic severely disrupted economic activities, and the initial unemployment insurance claims in the U.S. reached more than 11 million in April 2020.

For the year of 2019, we determine a sample of high valuation firms as those in the top 30% ranking of stocks by the market-to-book ratio. Within these high valuation firms, we define an indicator variable that equals one if the firm drops from the top 30% during the end of the first quarter of 2020, which experienced the most serious effects of Covid-19 and the market downturn.[6] We then examine whether firms' job posting rates predict overvalued firms using the logit and probit models. Table 4 documents the results. Panel A of 4 is based on the logit model, and Panel B is based on the probit model.

Based on the logit model, job posting rates are negatively and significantly associated with the stocks which dropped off the high valuation category during the Covid-19 period at the 10% level. That is, firms with low job posting rates are more likely to drop off the highly valued category of stocks. The point estimate is markedly larger than the baseline estimate in Table 3. The sample size is significantly smaller than our baseline results, and thus the point estimates are significant at the 10 percent level. Columns (2) and (3) of Panel A include capital investment rate and R&D, alongside the job posting rate. Column (4) includes all three independent variables. The coefficient estimates of capital investment rate and R&D are insignificant, suggesting that the capital investment rate and R&D cannot separate highly- from overly-valued stocks during the crisis period. The magnitude of the point estimate of the job posting rate remains similar when the other two variables are included. Furthermore, we control for firms' ESG ratings, which are shown to be important stock return predictors during the Great Financial Crisis (Lins et al., 2017) but not during the Covid-19 pandemic (Demers et al., 2021). We find that high ESG ratings are associated with a lower probability of dropping off the highly valued category of stocks. Controlling for the different ESG ratings, the point estimates on job posting rates continue to be negative

[6]Using the plummet of the stock market to study Covid-19 effect has been employed in the literature (e.g., Fahlenbrach et al., 2021; Ding et al., 2021; Wu, 2020)

and are significant at the 5% level.

In the probit model (Panel B), job posting rates are also negatively and significantly associated with falling off the high valuation category during the Covid-19 period at the 10% level. Column (2) includes job posting rates and capital investment, and Column (3) includes job posting rates and R&D investment rates as the independent variables. The magnitudes of the job posting point estimates are similar to those in the standalone regressions. When all the three control variables are included, the coefficient estimates on the job posting rates are still negative and statistically significant at the 10% level. When we control for the firms' ESG ratings, the point estimates on job posting rates continue to be negative and are significant at the 5% level.

4.2 Portfolio Approach

An alternative approach to determining whether firms' labor demand separates highly-valued firms that are fundamentally sound from those that are overvalued by investors is by forming job posting portfolios. Specifically, for each year, we form portfolios by assigning the highly valued (top 30%) firms into deciles (or quintiles) portfolios based on increasing posting rates. Then, we compute for each portfolio the percentage of stocks that dropped off the high valuation (top 30%) group. Table 5 reports the results. Panel A of Table 5 reports results based on decile portfolios and Panel B is based on quintile portfolios.

Panel A of Table 5 shows that the percentage of firms that dropped off the highly valued group – that is, *overvalued firms* – decreases monotonically from the low job posting rate portfolio (1) to the high job posting rate portfolio (10). For the two-year ahead horizon, 38.0% of the firms dropped off portfolio (1) with the lowest job posting rates, whereas only 20.0% of the firms fell out of portfolio (10) with the highest job posting rates. The decrease in the percentage drop off is almost monotonic from the lowest to the highest portfolios, based on job posting rates. The difference between the lowest and highest portfolios based on job posting rates is 18.0%, statistically significant. For the three-year ahead horizon, 42.3% of the firms dropped off the portfolio with the lowest job posting rates—43% of the highly-valued firms in this portfolio were overvalued—while only 21.1% of the firms dropped out of the portfolio with the highest job posting rates. The decrease in the percentage is again almost monotonic from the lowest to the highest portfolios based on job posting rates. Thus, the percentage of overvalued stocks among the lowest job posting firms was about 40%, whereas among high job posting firms only half (20%) were overvalued. A significant difference indeed.

Panel B of Table 5, based on quintiles of increasing job postings, shows a similar pattern: the percentage of firms dropping off the highly valued category decreases from the low job posting portfolio (1) to the high job posting portfolio (10) almost monotonically. The magnitude of percentage decreases is roughly similar to the deciles in Panel A.

We thus confirm that firms' labor demand, measured by the job posting rates, separates stocks that are highly valued by investors and have superior performance, from those that are overvalued by investors, and bound to substantially drop in price. To the best of our knowledge, this finding is first reported here.

4.3 Additional Tests

We further examine whether the job posting's predictive ability comes from within the industry or across industry variations, by repeating the portfolio approach controlling for industry effect. Specifically, we assign each highly valued firm (top 30% MB) to one of the five Fama-French industries. Then, within each industry, we rank firms on increasing job posting rates and form portfolios. Finally, we form five portfolios where portfolio 1 includes all the firms in the first portfolio of the five industries, portfolio 2 includes all the firms included in the second portfolio of the five industries, and so on, and then calculate the average percentage of firms that dropped off the highly valued group. This method removes inter-industry effects. The remaining differences across the five portfolios come from within-industry variations. Table 6 reports the average drop-off rates across the five industries.

For the two-year ahead horizon, 34.0% of the firms dropped off the highly valued group in the portfolio with the lowest job posting rates (1), while only 19.9% of the firms fell off the highly valued group for the portfolio with the highest job posting rates (10). The decrease in the percentages is almost monotonic from the lowest to the highest portfolios based on job posting rates, and very similar to the data in Table 4, indicating that a large portion of the job posting effect comes from within industry variations, thereby highlighting the importance of data on firm-level labor demand like ours vs. industry-level jobs data.

We also examine whether the predictability effects of job postings survive after controlling for R&D. Specifically, we assign each highly valued firm (top 30% MB) to tercile portfolios based on increasing R&D spending (relative to total assets). Then, within each R&D portfolio, we sort firms into terciles based on increasing job posting rates. Finally, we calculate the average percentage of firms that dropped from the highly valued group in each of the 3×3 cells within the next two or three years. Table 7 documents the results. For the two-year ahead horizon in the lower R&D spending group (1), 38.8% of the firms dropped out of the portfolio with the lowest job posting rates (1), while only 29.3% of the firms in this R&D class fell out of the highly valued group from the portfolio with the highest job posting rates. The decrease in the percentage is almost monotonic from the lowest to the highest portfolios based on job posting rates. We find the same pattern for each of the three R&D groups as well as for the three-year ahead horizon. These results indicate that the predictive ability of job posting for overvalued stocks survives after controlling for R&D spending.

Next, we examine if the predictive ability of job posting rates holds after controlling for long-term analyst forecasts. This is an important test since analysts are widely believed to be experts, able to identify overvalued stocks. Accordingly, we assign each of the top 30% firms into tercile portfolios based on increasing long-term analyst forecasts. Then, within each analyst long-term forecast group, we sort firms into terciles based on their increasing job posting rates. We once more calculate the average percentage of firms that dropped from the highly valued group in each 3×3 portfolio. Table 8 documents the results. For the two-year ahead horizon in the low analyst long-term forecast group (top line), 29.2% of the firms dropped off the highly valued group in the portfolio with the lowest job posting rates, and 29.5% of the firms with the highest posting rates dropped off the highly valued group. There is no incremental predictive power of job posting in this case. A certain predictive-ability of job posting exits for the middle group of analysts' forecasts (28.5% vs. 22.4%), while for the high analyst long-term forecast group (3), 29.7% of the firms dropped off the highly valued group in the portfolio with the lowest job posting rates, whereas only 17.0% of the firms fell out from the portfolio with the highest job posting rates. We find a similar pattern for the three-year ahead horizon. These results indicate that the job posting rates work well in differentiating the highly-valued firms from the overvalued ones for firms with optimistic analyst forecasts (medium and high long-term forecasts). Analysts issuing pessimistic earnings forecasts apparently internalize the job posting message.

Lastly, we test whether the job posting's predictive ability exists after controlling for firms' earnings management. This is an important test since Jensen (2004) predicted that managers of overvalued firms would manipulate sales and earnings to mask their overvaluation from investors and prolong it. The question here is whether job posting data are more robust to managerial manipulation than accounting data. To examine this, we assign each highly valued firm (top 30% of MB ratio) into tercile portfolios based on the extent of the most recent firms' earnings management, measured by the AEM indicator, which is the average of three commonly-used accruals measures (see Appendix A). Then, within each earnings management portfolio, we sort firms into terciles of their current job posting rates. We again calculate the percentage of firms that dropped from the highly valued group in each portfolio. Table 9 documents the results. For the two-year ahead horizon in the lower earnings management group, (1), 39.6% of the firms dropped off the highly valued group in the portfolio with the lowest job posting rates. In comparison, only 26.6% of the firms fell off the group from the portfolio with the highest job posting rates (3). The decrease in the drop off percentages is monotonic from the lowest to the highest portfolios based on job posting rates. We find the same pattern for each earnings management group and for the three-year ahead horizon as well. These results indicate that the predictive-ability of job posting with respect to overvalued stocks holds despite the firms' earnings management efforts. Since most analysts are by now familiar with the hazards of earnings management, this finding provides them with an additional tool for securities analysis.

We conclude that job posting data differentiates between highly-valued and overvalued stocks after controlling for various firm attributes (leverage, loss, etc.), predictors of future firm performance, such as R&D and the BM ratio, and analysts' earnings forecasts. The question now is: What is the reason underlying this ability of job postings to separate overvalued from highly-valued stocks? The following analyses will show that the reason for this separation of power is the fundamental ability of job posting data to predict firm performance.

5 Sales and Gross Profit Prediction by Job Postings

Panel A of Table 10 presents the estimates from regression (2), predicting one, two, and three years of annual sales growth (relative to a year earlier), using job posting rates, as well as capital expenditures and R&D intensities (scaled by total assets). In the standalone regressions, (1) – (3), we find that job posting rates are significantly and positively related to future sales growth. The economic magnitude of the job posting effect is substantial. At the one-year horizon, the coefficient estimate on the posting rate is 1.017 (top line). A one-standard-deviation increase in the job posting rate (0.024) is therefore associated with a 0.024 (=1.017 $\times$ 0.024) increase in the sales growth rate, which is 21.6% (=0.024/0.113) of its sample average. At the two-year horizon, a one-standard-deviation increase in job posting rate is associated with a 0.042 increase in sales growth rate, namely, the percentage of the sample average. On the other hand, the capital investment and R&D investment rates are not significantly associated with future sales growth beyond the first year (columns 4-9). The right three columns of Panel A report the results of the multivariate regressions with job posting rate, as well as capital investment and R&D investment rates. The results are consistent with those of the standalone regressions, with the magnitudes of the point estimates of the job posting rates somewhat lower than those of the standalone regressions. The coefficients of the capital investment and the R&D investment rates are still not statistically significant in years two and three.

Panel B of Table 10 presents the results of predicting future sales growth using job posting rates and the control variables, including firm size, the book-to-market (BM) ratio, leverage, loss indicator, cash position, and the contemporaneous sales growth. The definitions of the variables are in Appendix A. The left three columns report regression results based on the job posting rates and the control variables without controlling for firm fixed effects. The coefficient estimates of the job posting rates are statistically significant and positive for all horizons. The magnitudes of the estimates are, as expected, smaller than those in the standalone regressions. The next three columns of the panel, (4) – (6), report regressions based on the job posting rates and control variables, controlling for firm fixed effects. Here, only the coefficient estimates of the job posting rates for the one-year horizon are significant. The right six columns of the panel (7 – 12) report regression results, including both capital investment and R&D investment rates. The coefficient estimates of the job posting rates remain statistically significant and positive for all horizons in the regressions without firm fixed effects, and statistically significant and positive for the one-year horizon after controlling for firm fixed effects. Note that in this specification, with the control variables and firm fixed effects, the coefficient estimates on capital expenditures are not statistically significant in any of the horizons, while the coefficient estimates on R&D are even negative and weakly significant for the two-year horizon.

Panel A of Table 11 shows the results of predicting one, two, and three years ahead *gross profit change* (relative to a year earlier), using the job posting rate, capital expenditure, and R&D investment rates. In the standalone regressions, the job posting rates significantly and positively predict future gross profit rates for the three years ahead. For example, at the one-year horizon, a one-standard-deviation increase in job posting rate is associated with a 0.024 increase in gross profit growth, which is 23.3% of its sample average. The capital expenditures rate does not significantly predict future gross profit growth at any of the horizons (columns 4-6), while the R&D investment significantly and positively predicts gross profit growth (columns 7-9). The right three columns (10 – 12) document the results of the multivariate regressions with job posting rate, capital investment, and R&D investment rates, which are consistent with the estimates of the standalone regressions. The magnitudes of the point estimates of the job posting rates are similar to those of the standalone regressions.

Panel B of Table 11 shows the results of predicting future gross profit growth using job posting rate and control variables. The left three columns report regression results based on the job posting rates and control variables without controlling for firm fixed effects. The coefficient estimates of the job posting rates are statistically significant and positive for years 1 and 2. The next three columns of the panel, (4 – 6), control for firm fixed effects. The coefficient estimates of the job posting rates are statistically significant and positive *for all horizons*. The magnitudes of the estimates are, as expected, smaller than those in the standalone regressions. For example, the coefficient estimate of the one-year ahead regression is 0.482, compared to 1.012 in the standalone specification (Panel A). The right six columns of the panel (7 – 12) report regression results, including both capital investment and R&D investment rates, as well as the control variables. Here, the coefficient estimates on the job posting rates remain statistically significant and positive for all horizons in the regressions with firm fixed effeascts (columns 10 – 12), and statistically significant and positive for the one-year horizon without firm fixed effects. The coefficient estimates on capital expenditures are weakly significant in some of the regressions, and the coefficient estimates on R&D are not statistically significant in any of the regressions.

In untabulated results, we perform robustness tests by estimating the regression model (2) using the *quarterly* job posting data, rather than the annual job posting rates. The sample size increases significantly, and we nevertheless find consistent results as the main annual analyses reported above. Overall, we find that job posting rates significantly and positively predict future firm performance, incrementally to conventional indicators of enterprise performance and growth. This predictive-ability of job posting rates explains their capacity to separate overvalued from highly-valued stocks established earlier.

5.1 Additional Tests

In additional analyses, we examine the predictive ability of job posting rates across firms with different characteristics. We first categorize firms into employing high and low skill subgroups and investigate the performance predictability of job posting rates within the two subsamples. We show that the results are markedly stronger for high-skill firms. Then, we categorize firms into high and low employee productivity subgroups, where employee productivity is measured as earnings divided by the most recent number of employees. We document that job posting data better predict firm performance for high employee productivity firms.

5.1.1 High Skill vs. Low Skill Firms

For each year, we split the sample into high-skill and low-skill subgroups. A firm is classified as a high-skill firm if its employee job *skill requirements* are above the sample median in that year. We define the skill requirement of a firm as the share of high skill postings to all the postings for the firm, where high skill is defined as requiring at least a bachelor's degree or five years of experience. Then, we examine the performance predictability of job posting rates within the skill subsamples. Table 12 summarizes the results. Panel A of Table 12 documents the results based on sales growth rates, and Panel B refers to gross profit growth.

Panel A shows that the performance predictive-ability of posting rates for sales growth is stronger for the high skill firms (columns 1-6) compared to the low skill ones (columns 7-12), even when firm fixed effects are controlled for. In the standalone regressions (columns 1-2), the magnitudes of the point estimates are markedly larger for the high skill firms relative to the low skill firms (7-8). For the two-year ahead horizon, the point estimate of the high skill subgroup is 5.97, and the point estimate for the low skill subgroup is only 1.15, while for the three-year ahead horizon, the point estimate of the high skill subgroup is 9.01, relative to 2.34 for the low skill subgroup. The point estimates of the high skill subgroup are generally significant at the 1% level, while the point estimates of the low skill subgroup are significant only at the 10% level. The estimates, including the control variables (5-6), are significant for the 3-year ahead only. Panel B of Table 12 shows similar results to Panel A for predicting gross profit growth. Here too the predictive ability of job posting data is stronger for high skill firms.

5.1.2 Employee Productivity

We categorize firms into high and low employee productivity subgroups. A firm is classified as having high employee productivity if its employee productivity is above the sample median in that year. We define employee productivity as earnings divided by the most recent number of employees and examine the performance predictability of job posting rates within the employee productivity subsamples. Table 13 summarizes the results. Panel A of Table 13 documents the results based on sales growth rates and Panel B of Table 13 is based on gross profit growth. Panel A of Table 13 shows that the performance predictability of posting rates for sales growth is stronger for firms with high employee productivity (columns 1-6), compared to the low employee productivity ones (columns 7-12).

The point estimates of the high employee productivity subgroup are generally significant at the 5% level, even when all the control variables are considered (5 – 6). Panel B of Table 13 shows similar results to Panel A for predicting gross profit growth.

6 Conclusion

We demonstrate in this study the power of a new alternative data – corporate online job postings – to separate highly valued firms from overvalued ones: firms with high job posting rates are more likely to stay in the highly valued group (top 30% MB), whereas low job posting firms tend to significantly drop in value. Furthermore, we show that information contained in firms' online job postings predicts firms' performance as measured by sales and gross profit growth rates. Our findings suggest that, in addition to identifying overvalued stocks, job posting data can enhance financial analysis and securities' valuation in general. The search for alternative (to financial report) data—a major occupation of fund managers—is a promising area for accounting researchers. Finally, having opened the paper with Amazon's example of a much higher PE ratio (72) than Apple and Microsoft (19 and 27), we close by showing in Appendix C the job posting rates of the three firms. Consistent with our findings, the job posting rates of Amazon are substantially higher than those of Apple and Microsoft.[7] Amazon is, therefore, likely a highly-valued, rather than over-valued stock.

Lastly, we note a potential caveat of our study. Once our study becomes widely known, managers of over-valued firms trying to manage or justify over-valuation may inflate job postings. If online job postings are relatively costless, the power of our measure may be diminished when managers start manipulating online job postings.

Such manipulation is, however, short-term and self-defeating. In the current highly connected and open environment, a firm that systematically advertises for jobs but rejects all applicants will be identified and widely known. Such loss of credibility in the highly important and competitive labor market is quite costly.

[7]Note that we don't control here for the quality of employees searched.

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Table 1: Representativeness of Burning Glass Data

This table reports the summary statistics for the sample of job postings of firms listed on the major stock exchanges. The firms are grouped into 16 two-digit NAICS industries. The table also reports the distribution of Compustat firms across the same 16 industries. The sample includes 2007, and 2010-2017. All the continuous variables are winsorized at the top and bottom 1% levels. Variable definitions are in Appendix A.

Industry	# of Postings	# of Firms		Fraction
	BGT	BGT	Comp	BGT/Comp
Mining & Logging	452,639	97	224	43.30%
Construction	212,650	46	66	69.70%
Durable Goods	4,323,218	777	1108	70.13%
Non-Durable Goods	2,530,081	486	781	62.23%
Wholesale Trade	824,651	85	119	71.43%
Retail Trade	6,725,825	159	200	79.50%
Trans, Ware, and Util	1,418,972	100	176	56.82%
Information	3,738,519	407	635	64.09%
Finance and Insurance	5,818,988	556	905	61.44%
Real Estate & Rental	1,290,848	135	239	56.49%
Professional & Business	2,258,408	195	262	74.43%
Educational Services	123,767	15	28	53.57%
Health Care & Soc Assist	2,272,799	65	86	75.58%
Arts, Ent, & Rec	166,953	25	36	69.44%
Accommodation & Food	3,096,124	68	93	73.12%
Other Services	78,691	10	13	76.92%
Total	35,333,133	3,226	4,971	64.90%

Table 2: Summary Statistics

This table reports the summary statistics for the main sample. Appendix A has the definition of the variables. All the continuous variables are winsorized at the top and bottom 1% levels. Variable definitions are in Appendix A.

Variable	Obs	Mean	Std.	10%	25%	Median	75%	90%
ΔSales	17,020	0.113	0.332	-0.120	-0.015	0.063	0.165	0.352
ΔGross Profit	16,285	0.103	0.316	-0.143	-0.021	0.067	0.178	0.375
Job Posting	17,780	0.009	0.024	0.000	0.001	0.002	0.006	0.017
Capex	17,750	0.049	0.054	0.008	0.017	0.032	0.060	0.109
R&D	17,780	0.068	0.133	0.000	0.000	0.008	0.076	0.202
BM	17,299	0.476	0.422	0.094	0.215	0.391	0.650	0.971
Size	17,355	7.250	1.943	4.723	5.935	7.213	8.527	9.825
Leverage	17,970	0.232	0.219	0.000	0.025	0.196	0.354	0.527
Cash	17,760	0.254	0.345	0.017	0.049	0.137	0.317	0.605
Loss_dummy	18,413	0.195	0.396	0.000	0.000	0.000	0.000	1.000

Table 3: Predicting Overvalued Stocks

This table reports the results of using posting rates to predict whether firms are overvalued. First, for each year, we construct a sample of high valuation firms as those in the top 30% ranking of stocks by the market-to-book ratio, following Fama and French (1992). The market-to-book ratio is measured at the end of the previous fiscal year. Next, within the high valuation firms, we define an indicator variable $1_{overvalue}$ that equals one if the firm is no longer in the top 30% two years (or three years) later. Logit and probit models are reported. The "Effect on Prob." column to the right of the column reporting a given estimation indicates the marginal effect on the probability of dropping out implied by the coefficients from that estimation when the corresponding variable increases by 1. All the continuous variables are winsorized at the top and bottom 1% levels. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively. Variable definitions are in Appendix A.

Panel A: Logit	(1)	(2)	(3)	(4)	(5)	(6)	Effect on Prob.	
	2 yr	3 yr	2 yr	3 yr	2 yr	3 yr	2 yr	3 yr
Job Posting	-5.018***	-5.239***	-4.150***	-4.204***	-3.330**	-2.989*	-0.544	-0.580
	(-3.818)	(-3.716)	(-3.087)	(-2.905)	(-2.162)	(-1.866)		
Size					-0.121***	-0.110***	0.294	0.445
					(-4.763)	(-4.211)		
BM					5.981***	4.921***	-0.136	-0.177
					(20.135)	(16.484)		
Leverage					2.776***	2.537***	-0.020	-0.021
					(12.710)	(10.982)		
Loss_dummy					0.169	0.214	0.978	0.956
					(1.349)	(1.578)		
Cash					-0.197	-0.225*	0.454	0.493
					(-1.523)	(-1.669)		
Capx			0.337	0.651	1.797***	2.293***	0.029	0.044
			(0.610)	(1.119)	(2.723)	(3.336)		
R&D			-1.749***	-1.626***	-0.834**	-0.913**	-0.032	-0.044
			(-8.217)	(-7.163)	(-2.420)	(-2.539)		
Constant	-0.791***	-0.542***	-0.614***	-0.405***	-1.837***	-1.380***		
	(-22.162)	(-14.195)	(-11.765)	(-7.274)	(-7.482)	(-5.478)		
Obs	4,345	3,475	4,334	3,466	3,931	3,136		

Panel B: Probit	(1)	(2)	(3)	(4)	(5)	(6)	Effect on Prob.	
	2 yr	3 yr	2 yr	3 yr	2 yr	3 yr	2 yr	3 yr
Job Posting	-2.832***	-3.030***	-2.241***	-2.285***	-2.204***	-1.863**	-0.652	-0.617
	(-3.937)	(-3.831)	(-3.046)	(-2.826)	(-2.593)	(-2.052)		
Size					-0.084***	-0.073***	0.307	0.441
					(-5.914)	(-4.842)		
BM					2.929***	2.705***	-0.153	-0.174
					(21.990)	(17.764)		
Leverage					1.448***	1.461***	-0.025	-0.024
					(12.095)	(10.989)		
Loss_dummy					0.105	0.130*	0.866	0.895
					(1.504)	(1.660)		
Cash					-0.120*	-0.135*	0.428	0.484
					(-1.684)	(-1.751)		
Capx			0.178	0.369	1.037***	1.331***	0.032	0.045
			(0.536)	(1.037)	(2.714)	(3.272)		
R&D			-0.991***	-0.941***	-0.519***	-0.526***	-0.036	-0.045
			(-8.473)	(-7.319)	(-2.736)	(-2.590)		
Constant	-0.492***	-0.340***	-0.389***	-0.258***	-0.826***	-0.713***		
	(-22.879)	(-14.492)	(-12.373)	(-7.586)	(-6.279)	(-5.032)		
Obs.	4,345	3,475	4,334	3,466	3,931	3,136		

Table 4: Predicting Overvalued Stocks During Covid

This table reports the results of using posting rates to predict whether firms are overvalued during the Covid period. First, for 2019, we construct a sample of high valuation firms as those in the top 30% ranking of stocks by the market-to-book ratio, following Fama and French (1992). The market-to-book ratio is measured at the end of the previous fiscal year. Next, within the high valuation firms, we define an indicator variable $1_{overvalue}$ that equals one if the firm is no longer in the top 30% at the end of the first quarter of 2020, when the stock market plummeted. Logit and probit models are reported. All the continuous variables are winsorized at the top and bottom 1% levels. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively. Variable definitions are in Appendix A.

Panel A: Logit	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Job Posting	-21.167*	-19.193*	-21.124*	-19.236*	-59.609**	-53.499**	-54.236**
	(-1.791)	(-1.646)	(-1.783)	(-1.646)	(-2.315)	(-2.208)	(-2.199)
Capx		-4.791		-4.634			
		(-1.298)		(-1.245)			
R&D			0.401	0.241			
			(0.488)	(0.290)			
ESGScore					-0.019**		
					(-2.493)		
ESGCombinedScore						-0.008	
						(-0.942)	
ESG_index							-0.733***
							(-2.795)
Constant	-1.325***	-1.158***	-1.373***	-1.192***	-0.167	-0.752*	-0.758***
	(-10.136)	(-6.450)	(-8.351)	(-5.537)	(-0.415)	(-1.798)	(-3.883)
Obs	463	463	463	463	368	368	378
Panel B: Probit	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Job Posting	-9.880*	-9.245*	-9.991*	-9.334*	-32.977**	-29.163**	-30.006**
	(-1.947)	(-1.800)	(-1.950)	(-1.806)	(-2.381)	(-2.263)	(-2.252)
Capx		-2.822		-2.709			
		(-1.405)		(-1.330)			
R&D			0.266	0.153			
			(0.566)	(0.319)			
ESGScore					-0.011***		
					(-2.592)		
ESGCombinedScore						-0.005	
						(-0.973)	
ESG_index							-0.447***
							(-2.922)
Constant	-0.815***	-0.714***	-0.846***	-0.735***	-0.106	-0.470*	-0.466***
	(-11.155)	(-7.003)	(-9.240)	(-5.988)	(-0.439)	(-1.916)	(-3.996)
Obs	463	463	463	463	368	368	378

Table 5: High Valuation Attrition Rates by Job Postings

This table reports the average percentage of highly valued firms that dropped out from each portfolio two or three years later after the formation of the portfolios. Specifically, the portfolios are formed annually by assigning highly valued firms to deciles (Panel A) or quintiles (Panel B) based on their posting rates. Highly valued firms are defined as the top 30% of firms using the market-to-book ratio. A firm drops out from a portfolio if its market-to-book ratio is not in the top 30% two or three years later. All the continuous variables are winsorized at the top and bottom 1% levels. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively. Variable definitions are in Appendix A.

Panel A	Job Posting Deciles										
	1	2	3	4	5	6	7	8	9	10	10-1
% Dropped, 2 Years	Lowest									Highest	
Mean	0.380***	0.324***	0.296***	0.244***	0.248***	0.248***	0.244***	0.236***	0.226***	0.200***	-0.180***
t(Mean)	(8.659)	(21.405)	(10.533)	(8.238)	(9.425)	(13.095)	(14.292)	(11.164)	(19.183)	(23.057)	(-4.169)
% Dropped, 3 Years	Lowest									Highest	
Mean	0.423***	0.354***	0.341***	0.263***	0.258***	0.293***	0.264***	0.272***	0.266***	0.211***	-0.212***
t(Mean)	(12.972)	(9.052)	(8.976)	(7.665)	(12.604)	(15.430)	(14.635)	(11.191)	(24.885)	(9.043)	(-6.293)

Panel B	Job Posting Quintiles					
	1	2	3	4	5	5-1
% Dropped, 2 Years	Lowest				Highest	
Mean	0.352***	0.270***	0.248***	0.240***	0.213***	-0.139***
t(Mean)	(14.103)	(9.611)	(16.307)	(14.397)	(26.968)	(-5.191)
% Dropped, 3 Years	Lowest				Highest	
Mean	0.389***	0.302***	0.276***	0.268***	0.239***	-0.150***
t(Mean)	(13.412)	(8.728)	(42.424)	(17.771)	(15.097)	(-4.567)

Table 6: High Valuation Attrition Rates by Job Postings: Controlling for Industry

This table reports the same portfolios in Table 6 Panel B after controlling for industry effect. Specifically, highly valued firms are first assigned to quintiles within each of the five Fama-French industries. Then, within the same portfolio rank across the five industries, we perform the same analyses as in Table 6. All the continuous variables are winsorized at the top and bottom 1% levels. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively. Variable definitions are in Appendix A.

	Job Posting Quintiles					
	1	2	3	4	5	5-1
% Dropped, 2 Years	Lowest				Highest	
Mean	0.340***	0.285***	0.245***	0.251***	0.199***	-0.142***
t(Mean)	(12.509)	(12.251)	(38.130)	(15.992)	(14.730)	(-4.158)
% Dropped, 3 Years	Lowest				Highest	
Mean	0.370***	0.328***	0.262***	0.284***	0.224***	-0.146***
t(Mean)	(12.622)	(10.812)	(20.468)	(38.879)	(11.547)	(-4.843)

Table 7: Predicting Stock Overvaluation: Controlling for R&D

This table reports terciles portfolios double sorted based on R&D spending and posting rates. Specifically, highly valued firms are first assigned to terciles based on prior R&D spending. Then within each R&D portfolio, firms are sorted into terciles based on posting rates. The table reports the average fraction of highly valued firms that drop out from each portfolio one or two years later. All the continuous variables are winsorized at the top and bottom 1% levels. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively. Variable definitions are in Appendix A.

				Postings (Terciles)		
				1	2	3
		% Dropped, 2 Years		Lowest		Highest
	1	Mean	Lowest	0.388***	0.312***	0.293***
		t(Mean)		(8.66)	(10.36)	(23.03)
R&D	2	Mean		0.336***	0.261***	0.246***
		t(Mean)		(15.30)	(14.53)	(15.57)
	3	Mean	Highest	0.224***	0.181***	0.138***
		t(Mean)		(9.75)	(6.98)	(17.70)
		% Dropped, 3 Years		Lowest		Highest
	1	Mean	Lowest	0.454***	0.392***	0.336***
		t(Mean)		(10.04)	(18.17)	(15.96)
R&D	2	Mean		0.375***	0.285***	0.256***
		t(Mean)		(15.23)	(10.83)	(12.97)
	3	Mean	Highest	0.236***	0.218***	0.159***
		t(Mean)		(6.41)	(7.17)	(12.77)

Table 8: Predicting Stock Overvaluation: Controlling for Analyst Long-Term Forecasts

This table reports terciles portfolios double sorted based on analyst long-term forecast and posting rates. Specifically, highly valued firms are first assigned to terciles based on prior analyst long-term forecast. Then within each analyst long-term forecast portfolio, firms are sorted into terciles based on posting rates. The table reports the average fraction of highly valued firms that drop out from each portfolio one or two years later. All the continuous variables are winsorized at the top and bottom 1% levels. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively. Variable definitions are in Appendix A.

				Postings (Terciles)		
				1	2	3
		% Dropped, 2 Years		Lowest		Highest
	1	Mean	Lowest	0.292	0.274	0.295
		t(Mean)		(7.80)	(10.32)	(16.99)
Forecast	2	Mean		0.285	0.243	0.224
		t(Mean)		(12.25)	(13.27)	(5.91)
	3	Mean	Highest	0.297	0.220	0.170
		t(Mean)		(14.18)	(14.03)	(10.83)
		% Dropped, 3 Years		Lowest		Highest
	1	Mean	Lowest	0.308	0.300	0.318
		t(Mean)		(8,41)	(11.13)	(21.42)
Forecast	2	Mean		0.333	0.287	0.215
		t(Mean)		(8.19)	(16.88)	(6.69)
	3	Mean	Highest	0.339	0.242	0.190
		t(Mean)		(17.04)	(19.03)	(11.59)

Table 9: Predicting Stock Overvaluation: Controlling for Earnings Management

This table reports terciles portfolios double sorted based on earning management and posting rates. Specifically, highly valued firms are first assigned to terciles based on prior earning management (AEM). Then within each earning management portfolio, firms are sorted into terciles based on posting rates. The table reports the average fraction of highly valued firms that drop out from each portfolio one or two years later. All the continuous variables are winsorized at the top and bottom 1% levels. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively. Variable definitions are in Appendix A.

				Postings (Terciles)		
				1	2	3
		% Dropped, 2 Years		Lowest		Highest
	1	Mean	Lowest	0.396	0.308	0.266
		t(Mean)		(9.85)	(13.92)	(7.54)
AEM	2	Mean		0.287	0.253	0.234
		t(Mean)		(16.76)	(15.99)	(15.69)
	3	Mean	Highest	0.303	0.234	0.175
		t(Mean)		(16.13)	(19.94)	(13.62)
		% Dropped, 3 Years		Lowest		Highest
	1	Mean	Lowest	0.427	0.319	0.309
		t(Mean)		(11.15)	(13.05)	(9.24)
AEM	2	Mean		0.356	0.304	0.261
		t(Mean)		(9.17)	(15.06)	(16.03)
	3	Mean	Highest	0.311	0.235	0.205
		t(Mean)		(12.29)	(13.70)	(11.66)

Table 10: Forecasting Future Sales Growth by Job Postings

This table presents results using posting rate to predict firms' future sales growth. The regression specification is:

$$Y_{i,t+h} = \alpha + \beta \times Posting_{i,t} + Controls + \lambda_t + \gamma_i + \epsilon_t \tag{3}$$

where $Posting_{i,t}$ is the posting measures for firm i at time t and $Y_{i,t+h}$ is firm performance measures such as sales growth from time t to time $t+h, h = 1, 2, or\ 3$. λ_t is time fixed effect which remove unobserved common time shocks. γ_i is firm fixed effect which remove time-invariant firm characteristics. ϵ_t is the usual error term. The dependent variables are in percentage. All the continuous variables are winsorized at the top and bottom 1% levels. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively. Variable definitions are in Appendix A.

Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	1 yr	2 yr	3 yr	1 yr	2 yr	3 yr	1 yr	2 yr	3 yr	1 yr	2 yr	3 yr
Job Posting	1.017***	1.755***	2.931**							0.814***	1.575***	2.697**
	(4.715)	(3.578)	(2.413)							(3.935)	(3.321)	(2.282)
Capx				0.429***	0.304	0.225				0.293**	0.094	-0.156
				(3.663)	(1.243)	(0.506)				(2.433)	(0.390)	(-0.356)
R&D							0.379***	0.469	0.903	0.340**	0.437	0.910
							(2.762)	(1.633)	(1.540)	(2.462)	(1.529)	(1.553)
Obs.	16,485	14,258	11,894	16,478	14,251	11,886	16,485	14,258	11,894	16,478	14,251	11,886
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.294	0.442	0.561	0.296	0.442	0.562	0.295	0.442	0.561	0.300	0.444	0.565

Panel B	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	1 yr	2 yr	3 yr	1 yr	2 yr	3 yr	1 yr	2 yr	3 yr	1 yr	2 yr	3 yr
Job Posting	0.395***	0.745**	1.659**	0.598***	0.735	1.617	0.292**	0.678**	1.726**	0.549***	0.733	1.510
	(3.133)	(2.175)	(2.031)	(3.184)	(1.567)	(1.510)	(2.194)	(1.963)	(2.077)	(2.988)	(1.533)	(1.392)
Capx							0.245***	0.312**	0.348	0.176	0.250	0.590
							(4.006)	(2.085)	(1.154)	(1.523)	(1.123)	(1.569)
R&D							-0.012	0.023	0.633**	-0.099	-0.536*	-0.381
							(-0.244)	(0.186)	(2.313)	(-0.658)	(-1.714)	(-0.573)
Size	0.004***	0.003	-0.001	0.024***	-0.032	-0.122***	0.004***	0.002	0.002	0.021**	-0.041**	-0.134***
	(3.194)	(0.988)	(-0.197)	(2.783)	(-1.578)	(-3.009)	(2.704)	(0.798)	(0.318)	(2.455)	(-2.046)	(-3.403)
BM	-0.084***	-0.158***	-0.245***	-0.150***	-0.265***	-0.339***	-0.085***	-0.158***	-0.225***	-0.150***	-0.270***	-0.340***
	(-10.947)	(-10.186)	(-8.074)	(-9.685)	(-8.736)	(-6.285)	(-11.205)	(-10.302)	(-7.726)	(-9.607)	(-8.871)	(-6.244)
Leverage	0.011	0.019	0.087	-0.064	-0.291***	-0.460**	0.010	0.017	0.088	-0.065	-0.293***	-0.462**
	(0.721)	(0.488)	(1.121)	(-1.520)	(-3.356)	(-2.335)	(0.652)	(0.447)	(1.156)	(-1.554)	(-3.385)	(-2.346)
Loss_dummy	0.073***	0.162***	0.324***	0.070***	0.119***	0.184***	0.073***	0.162***	0.314***	0.072***	0.121***	0.191***
	(6.820)	(6.725)	(6.370)	(5.645)	(4.830)	(4.245)	(6.819)	(6.767)	(6.361)	(5.788)	(4.868)	(4.336)
Cash	0.163***	0.375***	0.723***	0.151***	0.308***	0.376***	0.169***	0.376***	0.587***	0.160***	0.367***	0.425***
	(10.490)	(10.651)	(9.813)	(5.257)	(5.707)	(4.029)	(9.497)	(9.052)	(7.038)	(5.375)	(6.343)	(4.391)
ΔSales	0.123***	0.202***	0.223***	-0.059***	-0.189***	-0.355***	0.119***	0.195***	0.207***	-0.057***	-0.186***	-0.350***
	(6.093)	(5.274)	(3.217)	(-2.697)	(-4.858)	(-5.016)	(5.883)	(5.113)	(2.965)	(-2.592)	(-4.721)	(-4.899)
Obs.	16,195	14,049	11,745	15,919	13,731	11,424	16,191	14,045	11,741	15,915	13,727	11,419
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Adj. R-squared	0.101	0.126	0.133	0.306	0.453	0.577	0.104	0.127	0.138	0.309	0.456	0.580

Table 11: Forecasting Future Gross Profit Growth by Job Postings

This table presents results using posting rate to predict firms' future gross profit growth. The regression specification is:

$$Y_{i,t+h} = \alpha + \beta \times Posting_{i,t} + Controls + \lambda_t + \gamma_i + \epsilon_t \quad (4)$$

where $Posting_{i,t}$ is the posting measures for firm i at time t and $Y_{i,t+h}$ is firm performance measures such as gross profit growth from time t to time $t+h$. λ_t is time fixed effect which remove unobserved common time shocks. γ_i is firm fixed effect which remove time-invariant firm characteristics. ϵ_t is the usual error term. The dependent variables are in percentage. All the continuous variables are winsorized at the top and bottom 1% levels. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively. Variable definitions are in Appendix A.

Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	1 yr	2 yr	3 yr	1 yr	2 yr	3 yr	1 yr	2 yr	3 yr	1 yr	2 yr	3 yr
Job Posting	1.012***	1.642***	2.371***							0.905***	1.527***	2.023***
	(5.103)	(4.132)	(3.199)							(4.690)	(3.940)	(2.809)
Capx				0.135	-0.020	0.420				-0.007	-0.276	-0.043
				(0.949)	(-0.075)	(1.140)				(-0.049)	(-1.071)	(-0.121)
R&D							0.411***	0.688***	1.486***	0.382***	0.681***	1.431***
							(3.504)	(2.914)	(3.922)	(3.229)	(2.881)	(3.721)
Obs.	15,764	13,637	11,390	15,761	13,634	11,387	15,764	13,637	11,390	15,761	13,634	11,387
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.251	0.388	0.537	0.250	0.386	0.536	0.252	0.388	0.539	0.253	0.390	0.540

Panel B	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	1 yr	2 yr	3 yr	1 yr	2 yr	3 yr	1 yr	2 yr	3 yr	1 yr	2 yr	3 yr
Job Posting	0.248**	0.527*	0.682	0.482***	0.867**	1.107**	0.198*	0.457	0.618	0.500***	0.863**	1.016**
	(2.259)	(1.800)	(1.206)	(2.716)	(2.407)	(2.228)	(1.778)	(1.543)	(1.077)	(2.794)	(2.385)	(2.047)
Capx							0.163**	0.228*	0.338	-0.063	0.154	0.579**
							(2.374)	(1.653)	(1.370)	(-0.448)	(0.665)	(1.965)
R&D							-0.068	-0.097	0.115	-0.092	-0.283	-0.357
							(-1.450)	(-0.845)	(0.518)	(-0.792)	(-1.353)	(-1.167)
Size	0.004***	0.003	-0.003	-0.004	-0.104***	-0.234***	0.003**	0.002	-0.003	-0.005	-0.108***	-0.242***
	(2.854)	(0.912)	(-0.531)	(-0.493)	(-5.428)	(-7.685)	(2.416)	(0.608)	(-0.628)	(-0.533)	(-5.559)	(-7.898)
BM	-0.082***	-0.143***	-0.177***	-0.174***	-0.287***	-0.370***	-0.084***	-0.146***	-0.175***	-0.176***	-0.290***	-0.373***
	(-10.031)	(-8.916)	(-6.717)	(-9.169)	(-8.342)	(-7.263)	(-10.241)	(-9.189)	(-6.829)	(-9.199)	(-8.394)	(-7.260)
Leverage	0.008	0.041	0.138**	-0.062	-0.301***	-0.550***	0.005	0.037	0.138**	-0.063	-0.304***	-0.552***
	(0.584)	(1.279)	(2.318)	(-1.565)	(-3.999)	(-4.410)	(0.378)	(1.150)	(2.318)	(-1.589)	(-4.023)	(-4.405)
Loss_dummy	0.080***	0.157***	0.214***	0.102***	0.161***	0.180***	0.080***	0.157***	0.212***	0.101***	0.162***	0.183***
	(7.466)	(7.186)	(5.814)	(7.374)	(6.485)	(5.111)	(7.495)	(7.224)	(5.833)	(7.394)	(6.549)	(5.189)
Cash	0.125***	0.311***	0.546***	0.179***	0.342***	0.512***	0.138***	0.329***	0.528***	0.188***	0.363***	0.531***
	(8.665)	(9.842)	(10.178)	(7.190)	(7.208)	(6.959)	(8.155)	(8.568)	(7.781)	(6.996)	(7.396)	(6.941)
ΔGrossProfit	0.094***	0.115***	0.204***	-0.050***	-0.186***	-0.302***	0.090***	0.111***	0.195***	-0.049***	-0.185***	-0.303***
	(5.940)	(4.278)	(4.672)	(-2.888)	(-6.557)	(-8.239)	(5.710)	(4.090)	(4.470)	(-2.820)	(-6.521)	(-8.286)
Obs.	15,417	13,384	11,214	15,159	13,077	10,893	15,416	13,383	11,213	15,158	13,076	10,892
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Adj. R-squared	0.065	0.086	0.099	0.263	0.418	0.567	0.066	0.087	0.100	0.263	0.418	0.568

Table 12: High Skill vs. Low Skill Firms

This table presents results using posting rate to predict firms' future sales growth within high skill firms and low skills firms subgroups. The regression specification is: $Y_{i,t+h} = \alpha + \beta \times Posting_{i,t} + Controls + \lambda_t + \gamma_i + \epsilon_t$, where $Posting_{i,t}$ is the posting measures for firm i at time t and $Y_{i,t+h}$ is firm performance measures such as sales growth from time t to time $t+h$. λ_t is time fixed effect which remove unobserved common time shocks. γ_i is firm fixed effect which remove time-invariant firm characteristics. ϵ_t is the usual error term. All the continuous variables are winsorized at the top and bottom 1% levels. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively. Variable definitions are in Appendix A.

Panel A: $\Delta Sale$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	High Skill Group						Low Skill Group					
	2 yr	3 yr	2 yr	3 yr	2 yr	3 yr	2 yr	3 yr	2 yr	3 yr	2 yr	3 yr
Job Posting	5.970***	9.007***	6.600***	10.605***	2.255	7.673***	1.153**	2.340*	0.894**	2.021*	0.702	1.394*
	(3.795)	(2.719)	(4.000)	(3.013)	(1.467)	(3.210)	(2.314)	(1.928)	(1.993)	(1.894)	(1.551)	(1.874)
Capx			-0.583	-1.263	-0.298	-0.092			0.214	0.015	0.185	0.353
			(-1.322)	(-1.350)	(-0.733)	(-0.103)			(0.741)	(0.029)	(0.641)	(1.028)
R&D			-0.120	-0.390	-1.095***	-1.516*			2.596***	5.092***	1.767**	4.217***
			(-0.376)	(-0.549)	(-3.163)	(-1.913)			(4.168)	(3.900)	(2.453)	(2.889)
Size					-0.052	-0.157**					-0.069***	-0.143***
					(-1.513)	(-1.965)					(-3.256)	(-4.142)
BM					-0.339***	-0.484***					-0.250***	-0.251***
					(-5.727)	(-4.319)					(-7.684)	(-5.111)
Leverage					-0.319***	-0.242					-0.398***	-0.521***
					(-2.586)	(-0.722)					(-3.362)	(-2.867)
Loss_dummy					0.221***	0.399***					0.031	0.009
					(5.057)	(4.424)					(1.220)	(0.264)
Cash					0.371***	0.336**					0.314***	0.520***
					(4.616)	(2.508)					(3.213)	(3.020)
ΔSales					-0.253***	-0.511***					-0.057	-0.256***
					(-5.001)	(-4.869)					(-0.904)	(-2.636)
Obs.	6,734	5,535	6,731	5,532	6,467	5,303	6,897	5,750	6,891	5,746	6,648	5,525
Year & Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.457	0.575	0.459	0.580	0.482	0.601	0.540	0.680	0.555	0.700	0.550	0.729

Panel B: $\Delta GrossProfit$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	High Skill Group						Low Skill Group					
	2 yr	3 yr	2 yr	3 yr	2 yr	3 yr	2 yr	3 yr	2 yr	3 yr	2 yr	3 yr
Job Posting	4.628***	6.849***	4.557***	6.346***	2.285**	1.926	0.922**	1.590*	0.752*	1.338*	0.678	0.898
	(3.927)	(3.016)	(3.796)	(2.777)	(2.247)	(1.161)	(1.995)	(1.898)	(1.652)	(1.672)	(1.472)	(1.456)
Capx			-0.190	0.692	0.231	1.375**			-0.322	-0.377	0.193	0.368
			(-0.480)	(1.135)	(0.620)	(2.451)			(-0.884)	(-0.801)	(0.573)	(0.956)
R&D			0.125	0.036	-0.304	-0.786**			2.707***	4.550***	1.194	2.045*
			(0.500)	(0.103)	(-1.286)	(-2.280)			(3.619)	(4.539)	(1.464)	(1.925)
Size					-0.126***	-0.286***					-0.113***	-0.237***
					(-4.369)	(-5.617)					(-4.119)	(-5.557)
BM					-0.332***	-0.531***					-0.286***	-0.298***
					(-5.997)	(-5.914)					(-6.505)	(-4.830)
Leverage					-0.349***	-0.784***					-0.271**	-0.361*
					(-3.168)	(-4.270)					(-2.465)	(-1.954)
Loss_dummy					0.181***	0.195***					0.142***	0.158***
					(4.955)	(3.358)					(4.222)	(3.379)
Cash					0.292***	0.488***					0.344***	0.504***
					(4.440)	(5.042)					(3.398)	(3.299)
ΔGrossProfit					-0.263***	-0.410***					-0.167***	-0.291***
					(-5.536)	(-7.158)					(-4.406)	(-5.381)
Obs.	6,237	5,146	6,237	5,146	5,972	4,908	6,793	5,658	6,790	5,655	6,527	5,418
Year & Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.452	0.604	0.452	0.605	0.487	0.634	0.402	0.551	0.412	0.564	0.439	0.586

Table 13: High vs. Low Employee Productivity Firms

This table presents results using posting rate to predict firms' future sales growth. The regression specification is: $Y_{i,t+h} = \alpha + \beta \times Posting_{i,t} + Controls + \lambda_t + \gamma_i + \epsilon_t$, where $Posting_{i,t}$ is the posting measures for firm i at time t. Employee productivity is the earnings for firm i at time t divided by the number of employees at time $t-1$. $Y_{i,t+h}$ is firm performance measures such as sales growth or gross profit growth from time t to time $t+h, h = 1, 2, or\, 3$. λ_t is time fixed effect which remove unobserved common time shocks. γ_i is firm fixed effect which remove time-invariant firm characteristics. ϵ_t is the usual error term. All the continuous variables are winsorized at the top and bottom 1% levels. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively. Variable definitions are in Appendix A.

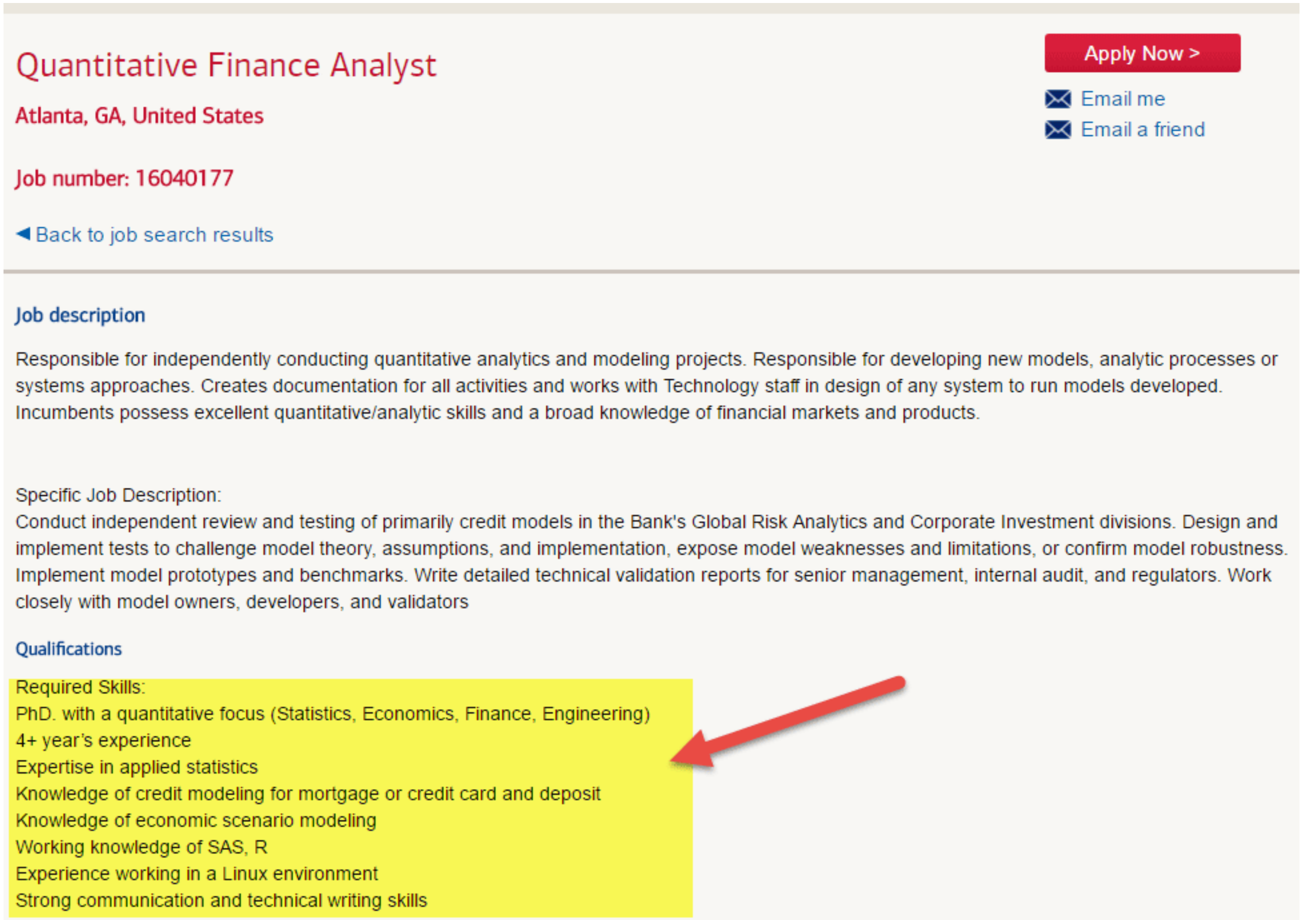
Panel A: $\Delta Sale$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	High Emp. Prod. Group						Low Emp. Prod. Group					
	2 yr	3 yr	2 yr	3 yr	2 yr	3 yr	2 yr	3 yr	2 yr	3 yr	2 yr	3 yr
Job Posting	2.381**	2.944**	2.213**	2.875**	1.853*	2.425**	0.902	1.560	0.917	1.524	0.268	0.817
	(2.430)	(2.561)	(2.303)	(2.497)	(1.956)	(2.091)	(1.393)	(0.878)	(1.413)	(0.862)	(0.418)	(0.443)
Capx			0.090	-0.138	0.197	0.324			0.019	-0.176	-0.082	0.338
			(0.390)	(-0.516)	(0.885)	(1.315)			(0.047)	(-0.214)	(-0.231)	(0.464)
R&D			0.907*	0.619	0.056	-0.473			-0.087	0.353	-0.944**	-0.617
			(1.820)	(1.037)	(0.124)	(-0.858)			(-0.230)	(0.436)	(-2.251)	(-0.680)
Size					-0.095***	-0.221***					-0.028	-0.120*
					(-3.875)	(-6.008)					(-0.948)	(-1.933)
BM					-0.400***	-0.491***					-0.232***	-0.269***
					(-7.588)	(-6.692)					(-6.132)	(-3.820)
Leverage					-0.174**	-0.365***					-0.291*	-0.317
					(-2.507)	(-3.538)					(-1.900)	(-0.832)
Cash					0.412***	0.517***					0.350***	0.329**
					(6.325)	(7.104)					(4.062)	(2.248)
ΔSales					-0.111**	-0.212***					-0.172***	-0.351***
					(-2.134)	(-3.933)					(-3.000)	(-3.420)
Obs.	6,835	5,724	6,835	5,724	6,776	5,668	6,309	5,121	6,305	5,116	6,132	4,975
Year & Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.497	0.623	0.499	0.623	0.523	0.646	0.479	0.597	0.481	0.601	0.501	0.618

Panel B: $\Delta GrossProfit$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	High Emp. Prod. Group						Low Emp. Prod. Group					
	2 yr	3 yr	2 yr	3 yr	2 yr	3 yr	2 yr	3 yr	2 yr	3 yr	2 yr	3 yr
Job Posting	2.068***	2.485***	1.929**	2.460***	1.579**	2.004**	0.857*	0.559	0.838	0.277	0.363	-0.122
	(2.580)	(2.909)	(2.538)	(2.890)	(2.164)	(2.333)	(1.680)	(0.682)	(1.644)	(0.336)	(0.852)	(-0.180)
Capx			0.031	-0.269	0.177	0.139			0.022	0.652	0.208	0.985*
			(0.114)	(-0.813)	(0.707)	(0.443)			(0.059)	(1.125)	(0.645)	(1.840)
R&D			0.797	0.494	-0.171	-0.846			0.077	1.015*	-0.707***	-0.631
			(1.552)	(0.793)	(-0.340)	(-1.464)			(0.234)	(1.729)	(-2.718)	(-1.330)
Size					-0.145***	-0.307***					-0.124***	-0.229***
					(-5.313)	(-8.273)					(-4.298)	(-5.015)
BM					-0.464***	-0.555***					-0.249***	-0.312***
					(-8.017)	(-6.953)					(-5.469)	(-4.639)
Leverage					-0.193**	-0.375***					-0.377***	-0.569**
					(-2.506)	(-3.119)					(-2.759)	(-2.486)
Cash					0.383***	0.444***					0.352***	0.492***
					(5.698)	(5.142)					(4.427)	(3.375)
ΔGrossProfit					-0.095***	-0.179***					-0.155***	-0.363***
					(-2.638)	(-4.204)					(-3.464)	(-6.072)
Obs.	6,830	5,722	6,830	5,722	6,747	5,646	5,766	4,684	5,765	4,683	5,552	4,505
Year & Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.455	0.579	0.456	0.579	0.492	0.603	0.444	0.586	0.444	0.589	0.479	0.629

Appendix A: Variable Definitions

Variable	Description
Job Posting rate	The number of job postings in a year scaled by the most recent total asset
ΔSales	Growth rate in sales over the year, calculated as current sales minus sales of the previous year scaled by previous year sales
ΔGrossProfit	Growth rate in gross profit (sales minus cost of goods sold) over the year, calculated as current gross profit minus gross profit of the previous year scaled by previous year gross profit
Capx	Capital expenditures scaled by the most recent total asset
R&D	R&D expenses scaled by the most recent total asset.
Size	Log market value of capital
Market-to-Book	For identifying highly-valued firms and is defined following Fama and French (1992): Book value of assets (Compustat AT) minus book value of equity plus market value of equity (Compustat PRCC_F $\times$ CSHO) divided by book value of assets (Compustat AT). Book value of equity is defined as stockholder's equity (Compustat SEQ) minus preferred stock plus balance-sheet deferred taxes and investment tax credit (Compustat txditc). If data item TXDITC is missing, it is set to zero. If data item seq is not available, it is replaced by either common equity (Compustat CEQ) plus preferred stock par value (Compustat PSTK), or assets (Compustat AT) $-$ liabilities (Compustat LT). Preferred stock is preferred stock liquidating value (Compustat PSTKL) (or preferred stock redemption value (Compustat PSTKRV), or preferred stock par value (Compustat PSTK)).
BM	Book equity (the differences of total assets and total liabilities) divided by market value of common equity (price times shares outstanding)
Leverage	The sum of long-term and short-term debt scaled by the most recent total asset
Loss_dummy	Indicator for negative earnings after adding back R&D
Cash	Cash and Short-Term Investments scaled by the most recent total asset
ESGScore	Refinitiv EIKON ESGScore for FY2018 from Demers et al. (2021).
ESGCombinedScore	Refinitiv Combined ESG score for FY2018 from Demers et al. (2021).
ESG_index	An extended version of the ESG scores in Lins et al. (2017), including all 7, rather than 5 categories, following Demers et al. (2021).
Emprod	Earnings divided by the most recent number of employees
Forecast	The average of analysts' long-term earnings forecasts in a year
AEM	The average of three measures of accrual based earnings management: the unsigned abnormal accruals computed using the Modified-Jones model from Dechow et al. (1995), the unsigned abnormal accruals computed using the methodology in Teoh et al. (1998), and the unsigned abnormal accruals computed as the absolute residual from the regression of changes in working capital accruals on past, present, and future cash flow realizations as per Dechow and Dichev (2002) model

Appendix B: Job Posting Example



Quantitative Finance Analyst

Atlanta, GA, United States

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Job description

Responsible for independently conducting quantitative analytics and modeling projects. Responsible for developing new models, analytic processes or systems approaches. Creates documentation for all activities and works with Technology staff in design of any system to run models developed. Incumbents possess excellent quantitative/analytic skills and a broad knowledge of financial markets and products.

Specific Job Description:
Conduct independent review and testing of primarily credit models in the Bank's Global Risk Analytics and Corporate Investment divisions. Design and implement tests to challenge model theory, assumptions, and implementation, expose model weaknesses and limitations, or confirm model robustness. Implement model prototypes and benchmarks. Write detailed technical validation reports for senior management, internal audit, and regulators. Work closely with model owners, developers, and validators

Qualifications

Required Skills:
PhD. with a quantitative focus (Statistics, Economics, Finance, Engineering)
4+ year's experience
Expertise in applied statistics
Knowledge of credit modeling for mortgage or credit card and deposit
Knowledge of economic scenario modeling
Working knowledge of SAS, R
Experience working in a Linux environment
Strong communication and technical writing skills

Appendix C: Amazon Job Posting Rates