# Labor Pains: The Impact of Labor Market Competition on Stock Returns


Ivan Indriawan, Shihe Li, Ralf Zurbruegg

*Adelaide Business School, University of Adelaide*


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**Abstract**

We introduce a novel approach to quantifying labor market competitiveness, focusing on the heightened competition arising from the increased demand for identical occupations. Using this metric, we find that an increase in labor market competitiveness leads to a decrease in aggregate market excess returns in the subsequent three to twelve months. This supports the concept of a "war for talent", with heightened labor market competitiveness leading to negative cash flow shocks, manifested through increased personnel-related expenditures and reduced cash holdings. We further find that firms that are more sensitive to labor market competition face higher risks and thus command a risk premium. Specifically, a portfolio that invests in stocks with a high sensitivity to labor market competition, or high 'competition betas,' yields higher returns than those with lower competition betas. These findings suggest that investors view a highly competitive labor market as a risk factor and demand higher returns for stocks with greater exposure to this risk.



**JEL Classifications***:* E2, E3, G1, J2, J3

**Keywords**: Return predictability, Job postings, Labor market competition, Talent wars

## 1. Introduction

Previous studies on the time-series predictability of aggregate returns have identified a multitude of variables that can influence stock market forecasting, including valuation ratios (Campbell and Shiller, 1988; Lewellen, 2004), interest rates (Fama and Schwert, 1977; Fama, 1981), default and term premiums (Keim and Stambaugh, 1986; Fama and French, 1989), and inflation (Fama and Schwert, 1977; Campbell and Vuolteenaho, 2004). More recent work, however, has begun to underscore the importance of labor market conditions in predicting aggregate stock returns (Kothari and O'Doherty, 2023).

In this study, we explore the predictive power of labor market competitiveness for aggregate return predictability. Labor as a primary driver of economic growth and fluctuation, plays a pivotal role in any production process. Firms do not operate in a vacuum when it comes to labor-related activities such as hiring (e.g., Postel‑Vinay and Robin, 2002; Cahuc, Postel-Vinay, and Robin, 2006). In fact, firms often interact with each other within the labor market, particularly when they demand similar types of labor. This competition for talent can impact firms' operating costs and profitability, which in turn can influence their stock prices. Consequently, the degree of competition in the labor market can offer valuable insights into stock market dynamics.

While there is reason to believe that an association exists between labor market competitiveness and expected market returns, the direction of this relationship remains uncertain. It is plausible that there is a positive association between labor market competitiveness and expected market returns. When firms share a demand for similar types of labor, they become more susceptible to common economic shocks. For example, if multiple firms rely heavily on certain occupations, they will experience similar fluctuations in labor market conditions, such as expansions or contractions in the availability of those occupations (Topel, 1986; Acemoglu and Autor, 2011). During such periods, the average correlation between stock returns tends to rise, resulting in a positive risk premium as a higher correlation reduces the benefits of diversification (Krishnan, Petkova, and Ritchken, 2009; Pollet and Wilson, 2010).

Conversely, it is also possible that the relationship between labor market competitiveness and expected market returns is negative. When competition for skilled employees intensifies, firms may find themselves allocating more resources towards attracting and retaining high-performing employees, often referred to as the 'war for talent' (Chambers et al., 1998). Kim (2022) provides evidence that firms in denser labor market networks tend to spend more on R&D and may face talent outflows when their labor market peers enhance their benefits for top employees. As a result, these firms may be compelled to increase their own employee benefits, leading to elevated costs and diminished firm valuations, resulting in lower stock prices. Moreover, Kothari and O'Doherty (2022) find that higher staff turnover, as measured by the ratio of job postings to employed workers, can trigger increased adjustment costs, ultimately reducing the expected stock market return. These findings suggest that labor market competitiveness can negatively impact a firm's cash flows and, consequently, its stock market returns.

In this study, we introduce a novel approach to measuring labor market competitiveness and investigate its relationship with aggregate stock market returns. We leverage a unique dataset provided by Burning Glass Technologies (BGT), which encompasses a vast majority of online job postings in the United States. As an employment data analytics firm, BGT collects data from online job boards and company websites daily, offering a wealth of information such as the employer's name, occupation title, job location, education, and skill requirements, among other data points. This granularity allows us to identify which occupations are currently in high demand and which ones are not. By utilizing this rich dataset, we can glean valuable insights into labor market competitiveness and its potential influence on stock market dynamics.

We adopt a methodology inspired by the information retrieval literature to measure labor market competitiveness, drawing upon works such as Sebastiani (2002) and Hoberg and Phillips (2016). Our approach involves calculating the monthly cosine similarity score between two firms that share a similar labor demand profile. This score is derived from comparing two vectors, each representing the occupations sought by the respective firms. A higher cosine similarity score indicates a stronger level of competition between the pair of firms in the labor market. To gain an overall assessment of labor market competition, we consider the cosine similarity scores across all possible firm pairs in the market and calculate the average value of these scores. As job postings are collected daily, the monthly competition measure is time-varying and reflects changes in firms' labor demand. The resulting value provides us with a quantifiable measure of prevailing competition in the labor market.

Our competition measure diverges from other labor market metrics employed in previous studies, such as the unemployment rate (Ludvigson and Ng, 2007), the employment growth rate (Chen and Zhang, 2011), and the job openings-to-employment ratio (Kothari and O'Doherty, 2023). While the unemployment rate reflects the proportion of individuals without employment in the labor force, and the employment growth rate represents the number of new jobs created, these metrics do not reflect the specific challenges that firms encounter when competing in the labor market. Similarly, the job openings-to-employment ratio primarily reflects employee turnover within firms but not the intensity of competition in hiring similar occupational categories. Our metric, therefore, offers a more nuanced perspective as it recognizes that certain occupations may be highly sought after, resulting in fierce competition among firms, while others may have lower demand, leading to reduced competition. By considering the relative demand for different job categories, our aggregate metric provides a more accurate assessment of the level of competition firms can anticipate when seeking to hire labor.

To validate our labor market competitiveness measure, we perform several tests. First, we evaluate the correlation between our measure and the labor market concentration index derived in a similar fashion to the Herfindahl-Hirschman index, i.e., calculated based on the share of vacancies of all the firms that post vacancies in the market. Our findings indicate a negative relationship between the two measures, i.e., as the labor market becomes concentrated, it becomes less competitive.[1] Second, we explore the link between our measure and the market average salary, uncovering a positive relationship. Higher levels of labor market competitiveness correspond to increased market average salaries, suggesting that individuals seeking employment possess greater market power when the labor market is more competitive.

For our formal analyses, we employ a predictive regression model and regress excess stock returns on lagged labor market competitiveness. Our findings reveal a negative relationship: higher levels of competition in the labor market correspond to lower aggregate market excess returns over the subsequent three to twelve months. The observed negative coefficients for lagged labor market competitiveness remain statistically significant even when accounting for other well-established predictors documented in the literature. This indicates that labor market competitiveness carries its own distinct predictive power for future stock returns. Furthermore, our analysis reveals that the negative relationship between labor market competitiveness and returns is more pronounced for a portfolio of small stocks compared to large stocks. This suggests that smaller firms are particularly susceptible to the impact of heightened levels of labor market competition.

We investigate the impact of labor market competitiveness on aggregate stock returns through different transmission channels. We utilize the return decomposition approach proposed by Campbell and Shiller (1988) to separate asset returns into discount rate and cash

[1] In Section 4.1., we explain why our labor market competitiveness measure is superior to the labor market concentration index.

flow shocks. We then regress these shocks on lagged labor market competitiveness. Our findings indicate that labor market competitiveness primarily affects the expected cash flows rather than the discount rate shocks. The negative cash flow shocks manifest in higher selling, general, and administrative (SGA) as well as research and development (R&D) expenditures, two main proxies for personnel-related expenses, accompanied by a decrease in firms' cash holdings. We also discover that these links are stronger for smaller firms. These results suggest that intensified labor market competition drives firms to allocate more resources toward hiring new employees or retaining high-caliber talents.

In the final part of our study, we delve into the economic implications of our finding that higher labor market competitiveness leads to lower returns. Specifically, we aim to determine whether investing in firms that are more responsive to labor market competition carries increased risk and commands a risk premium. To investigate this, we undertake analyses based on portfolio sorting. At the end of each year, we sort firms into double-sorted quintile portfolios based on their size and return sensitivity to our labor market competitiveness metric, which we refer to as the '*competition beta*.'

Following this, we track the performance of each portfolio over the following 12 months. We find that for the lower size quintile, firms with higher competition betas earn higher returns compared to firms with lower competition betas. The spread between the top and bottom quintiles of competition betas is 1.5% per month, equivalent to an annualized spread of 18%. We additionally evaluate the regression alphas across various asset pricing models, including the Fama and French (1996) three factors, Carhart (1997) momentum factor, Fama and French (2015) five factors, and the Hou, Xue, and Zhang (2015) q-factors. The results indicate that these alphas range between 1.1% and 1.5% per month. These results strongly support the hypothesis that our labor market competitiveness risk factor is indeed priced, particularly for the smaller firms who tend to be price-takers in the labor market. The positive and significant premium associated with this risk suggests that stocks with higher sensitivity to labor market competitiveness offer higher expected returns. This finding aligns with the notion that a highly competitive labor market is perceived as undesirable by investors, who consequently demand compensation for holding stocks with greater exposure to this risk.

Our study contributes to the growing field of literature that studies the interaction between labor and finance. Liu and Wu (2022) show that a firm's labor peers are vastly different from their industry peers. Returns of labor-linked firms strongly comove, and this comovement is larger when hiring is difficult. In contrast, the present study goes a step further by introducing a measure of aggregate labor market competition. We demonstrate that firm labor market linkages can be utilized to construct this measure, which provides insights into the overall level of competition within the labor market.

Our measure also differs from the concept of search costs discussed in previous studies. For instance, Belo, Lin, and Bazdresch (2014) examine the influence of labor market frictions on asset prices in the context of US firms. Their findings indicate that firms with high hiring rates experience lower future stock returns on average. These firms face higher search costs due to their expansion activities. Similarly, Kothari and O'Doherty (2023) discovered that the ratio of job postings to employment levels is a strong predictor of the aggregate equity premium. They show that job search activity is costly and associated with negative future market returns. Unlike the prior studies that primarily examined search costs, the current research centers on labor market competition, which can fluctuate independently of staff turnover. We show that increased competition in the labor market compels firms to spend more to retain top talent. This heightened expenditure has implications for the firms' future stock returns.

We organize the remainder of the paper as follows. Section 2 discusses the theoretical motivation for hypothesizing a link between labor market competitiveness and stock returns.

Section 3 discusses the data and explains the construction of our labor market competitiveness measure. Section 4 reports the empirical results. Section 5 concludes.

## 2. Hypotheses Development

### *2.1. Labor market competitiveness and stock returns*

Existing theories conflict on how labor market competitiveness affects firm value. The risk-return tradeoff suggests that security with a higher level of risk should earn a higher return. In the current setting, we hypothesize that commonality in the labor market leads to a greater correlation among stocks. This is based on the premise that a firm's business focus should be reflected by the people they hire (see, e.g., Darendeli, Law, and Shen (2022), who consider '*Green*' job postings as a reflection of a firm's environmental effort). When companies start to employ more employees with similar skill sets, the labor market becomes more concentrated and less diversified. As a consequence, those companies will become more susceptible to common market shocks. We can therefore expect that greater labor market commonality leads to greater correlation among stocks. An increase in asset correlations can lower diversification benefits for investors and increase aggregate market risk. Therefore, the average correlation should forecast stock market returns. Indeed, several studies have documented that average correlation positively forecasts future stock market returns (see, e.g., Krishnan et al., 2009; Pollet and Wilson, 2010).

The labor market frictions literature, on the other hand, suggests that in the presence of hiring frictions, replacing workers and adjusting employment levels in response to productivity changes are costly to firms. This is due to the resources required for searching and training new hires (Kuehn, Simutin, & Wang, 2017). Building upon this perspective, Kothari and O'Doherty (2023) assert that a measure reflecting firms' forward-looking intentions to hire new workers holds valuable information about expected aggregate stock market returns. To capture this intention, we focus on measuring the level of competition within the labor market. Unlike approaches that only consider the number of hirings, our method accounts for broader labor market conditions. For instance, it is possible for the labor market to become more competitive without an increase in total hiring. With an increase in labor market competitiveness, firms not only face higher costs associated with hiring new employees, but they must work more diligently to retain their existing workforce. This approach captures an additional dimension, offering a fresh perspective on comprehending the intricate relationship between labor market dynamics and expected aggregate stock market returns.

In summary, a highly correlated market is risky and thus demands higher returns. Alternatively, highly competitive labor markets pose greater challenges for firms, resulting in lower stock returns. Given these opposing viewpoints, our first hypothesis is:

**H1:** Higher labor market competitiveness impacts stock returns.

*2.2. Labor market competitiveness and small firms*

The dynamics of the labor market present distinct challenges for large and small firms, impacting their ability to attract and retain talent. In this context, larger firms tend to hold a unique position as price makers in the labor market. Due to their size, established reputation, and resources, larger corporations are often able to set competitive compensation packages, offer attractive benefits, and provide robust career progression opportunities (see, e.g., Brown and Medoff, 1989; Brown et al., 1990; Troske, 1999). These advantages, along with the perceived stability and growth potential of larger firms, make them attractive to job applicants.

In contrast, smaller firms typically operate as price-takers in the labor market, which means they have less bargaining power when it comes to attracting and retaining talent. Smaller firms must, therefore, differentiate themselves to attract talent. They may offer easier access to work opportunities, greater employee benefits tailored to individual preferences, or unique value propositions, such as a strong commitment to sustainable practices. In addition, small firms are often associated with new entrants to the markets. The vast majority of new firms are short-lived (Geroski, 1995; Shane, 2009). Thus, accepting employment in a new venture carries inherent risk. These factors suggest that smaller firms face greater challenges when the labor market is competitive. We, therefore, hypothesize that:

**H2:** Labor market competitiveness has a greater impact on small firms compared to larger firms.

## 3. Data

### *3.1. Burning Glass Technologies*

We obtain job listings and their characteristics from Burning Glass Technologies (BGT), an analytics company that tracks online employment data. Starting in 2007, the company extracts job postings listed on more than 40,000 online job boards and company websites.[2] BGT parses and deduplicates (i.e., removes repeated postings that may concurrently appear on several job platforms) the postings into a machine-readable form, creating a comprehensive dataset for labor market analysis. We obtained these posting-level data for the years 2010 through 2021.

The BGT database captures nearly all online job postings, which presents a significant advantage over databases relying on a single source, such as CareerBuilder.com and Monster.com. An alternative popular database, the Job Openings and Labor Turnover Survey (JOLTS) by the U.S. Bureau of Labor Statistics asks a nationally representative sample of employers of vacancies they wish to fill in the near term. However, JOLTS data is typically

[2] The database lacks postings from 2008 and 2009.

available only at an aggregated level and contains relatively limited information on the characteristics of the vacancies. In contrast, BGT data is rich in detail. For each listing, BGT collects the full text of the job posting, the date of posting, the employer's name, the vacancy's location, and a range of algorithmically imputed variables constructed from the text of the job posting, such as the occupation to which the vacancy belongs to, the skills, minimum level of education, and prior experience required, as well as estimated wages, among over seventy possible standardized fields. Given this advantage, the BGT data have been used in recent studies, including Hershbein and Kahn (2018), Deming and Noray (2020), and Darendeli, Law, and Shen (2022).

Despite its richness, the BGT data does have a few shortcomings. First, the dataset only covers postings on the internet. Although job postings have increasingly moved online, there could be concerns that the types of jobs posted online are not representative of all job openings. To assess this, Hershbein and Kahn (2018) compare the industry-occupation mix of vacancies in BGT relative to other sources such as JOLTS, the Current Population Survey, and the Occupational Employment and Wage Statistics. They find that while BGT postings tend to be skewed toward more highly-skilled occupations, the occupational and industry distributions remain stable over time and comparable to the aggregate trends in other sources. Second, job postings can remain unfilled. As a result, the number of job postings can be higher than the number of actual hires. While we do not have information on whether job postings are eventually filled, a recent study by Law and Shen (2021) validated BGT job postings data using employee resumes and H1B visa application data. They found the postings in BGT to be a reasonable proxy for firms' actual hiring.

While the BGT database provides occupation and employer names in job postings when available, about 40 percent of the postings lack the employer name. This is primarily due to the postings being listed on recruiting websites that often withhold the employer's name. We exclude these job posts from our study. A key step in our research involves matching the BGT dataset to the firm list from Compustat and subsequently linking it with the stock data from the Center for Research in Security Prices (CRSP). Given that the employer name is the only identifier available in BGT, we employ both machine- and manual-matching procedures to align the firm and its subsidiaries' names in Compustat. To ensure the accuracy of the match, we use a fuzzy matching approach with a 95% threshold. Any matches that raise doubts are manually verified for accuracy. From the sample period of January 2010 to December 2021, we successfully match 26,237,819 BGT job postings to publicly traded companies in Compustat. Following this, we use the identifier gvkey in Compustat to link our dataset with the stock price data from CRSP.

Appendix A compares the distribution of firms across industry sectors for our matched BGT sample and the Compustat universe. Comparable to the firms in Compustat, most of the industry sectors are fairly represented in our matched BGT dataset. The top four industry sectors are Durable goods, Non-durable goods, Finance and Insurance, and Information. Overall, we find that the matched BGT sample is representative of the publicly listed firms on major US stock exchanges.

### *3.2. Measuring labor market competitiveness*

To measure aggregate labor market competitiveness, we first calculate a labor demand similarity score between pairs of firms. Our measure construction is underpinned by the assumption that firms competing in the same labor markets tend to seek employees within the same occupations. As more firms demand the same type of occupations, the labor market becomes more competitive. Our approach thus enables each firm’s competitors to be identified based on the similarity of the occupations they seek to hire. We utilize the occupation name based on the O*NET code in each posting.[3] Each month we construct a set of unique occupations available in the BGT dataset. On average, there are 800 unique occupations every month in our dataset based on the O*NET code. Since we group the job postings by month, the set of unique occupations varies from month to month. Hence, the set of unique occupations always reflects the current occupation list demanded by U.S. firms.

To measure the labor demand similarity between two firms, we calculate the cosine similarity score between their labor demand profiles.[4] Specifically, we construct the labor demand profile as a vector $O_{i,t}$, corresponding to occupations demanded by firm $i$ in month $t$. The length of the vector is the number of unique occupations demanded by all firms in month $t$. It is important to note that the information content of different occupations can vary. Occupations commonly demanded by a large number of firms (e.g., customer service representatives) contain less information about a specific company than unique occupations demanded by a small number of firms (e.g., business intelligence analysts). Therefore, using the raw count of job postings for each occupation does not adequately capture the information contained in the demand for a given occupation. This concern is echoed in the information retrieval literature, which suggests that common words are less informative than unique words. To address this, we apply weighing schemes to adjust the raw count of job postings for each occupation (see, e.g., Loughran and McDonald, 2011). Specifically, we assign each element of $O_{i,t}$ to measure the weighted demand for the corresponding occupation. The $k^{th}$ element of $O_{i,t}$ for firm $i$ in month $t$ is denoted as $o_{i,k,t}$ and is defined as follows:

[3] O*NET is a classification of job titles widely used in labor economic studies. O*NET is the nation's primary source of occupational information, including worker attributes and job characteristics. It contains descriptions of over 1000 occupations, covering the entire U.S. economy. Just like the SIC codes for industry classifications, O*NET provides a common language for defining and describing occupations and job requirements. Website: https://www.onetcenter.org/.

[4] For a detailed review of related methods, see Sebastiani (2002). For a discussion on the empirical advantages of the cosine similarity method, see Hoberg and Phillips (2016).

$$o_{i,k,t} = \begin{cases} \frac{1+\log(p_{i,k,t})}{1+\log(P_{i,t})} \cdot \log\left(\frac{N_t}{n_{k,t}}\right), & if\ p_{i,k,t} \geq 1 \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

where $p_{i,k,t}$ is the raw number of postings of the $k^{th}$ occupation by firm $i$ in month $t$, $P_{i,t}$ is the number of all job postings by firm $i$ in month $t$, $N_t$ is the total number of firms in the sample in month $t$, $n_{k,t}$ is the number of firms demanding at least one $k^{th}$ occupation in month $t$. The term $\frac{1+\log(p_{i,k,t})}{1+\log(P_{i,t})}$ captures the weight of each occupation while the term $\log\left(\frac{N_t}{n_{k,t}}\right)$ gives greater weight for job postings that are unique, relative to job postings that are common across all firms.

We define the labor demand similarity between firm $i$ and firm $j$ as the cosine similarity of their vectors $O_{i,t}$ and $O_{j,t}$:

$$Labor_{i,j,t} = \frac{O_{i,t} \times O_{j,t}}{\|O_{i,t}\| \times \|O_{j,t}\|}. \tag{2}$$

$Labor_{i,j,t}$ is a value between zero and one. If the measure is close to one, then there is a large overlap between the occupations demanded by the two firms. If it is close to zero, then the two firms demand very different labor inputs.

Up to this point, we have developed a labor similarity measure that is continuous and varies with time, calculated between each pair of firms on a monthly basis. This forms a labor link network that changes over time. Each firm can have its own distinct set of labor-linked firms, with some closer and others distant. However, it is not possible for a single firm to dominate the labor market and be linked to all other firms in terms of labor. We, therefore, impose a minimum threshold requirement. That is, we define firm $i$'s labor-linked firms as all firms $j$ with $Labor_{i,j,t}$ above a pre-specified minimum threshold. A high threshold will result in fewer labor-linked firms. Following the approach of Liu and Wu (2022), we choose a threshold that ensures the number of labor-linked firms does not exceed the number of firms in the same industry as the firm in question. The number of firms in the industry is based on our sample and can be grouped using the three-digit SIC industries (SIC3).[5] To mitigate the effect of firm size, for each firm, we compute the median similarity score of its pairwise similarity scores. We then subtract the median score from the firm's original pairwise similarity score before applying the minimum threshold. For each firm, we next compute the firm average similarity, $\overline{Labor_{i,t}}$. To calculate the aggregate labor market competition, we take the weighted average of firm-level similarities,

$$Competition_t = \sum_{i=1}^{N} w_{i,t} \cdot \overline{Labor_{i,t}}. \tag{3}$$

where $N$ is the number of firms in our sample in month $t$, and $w_{i,t}$ is the ratio of market capitalization for firm $i$ relative to the market total in month $t$. This value increases when there is a larger overlap in the occupations demanded by the overall market. This measure also varies with time, as different firms may demand different occupations in different months.

Table 1 reports the summary statistics of our labor market competitiveness measure over the sample period. The measure ranges from a minimum of 0.211 to a maximum of 0.294, with a mean of 0.262. It is negatively skewed, with only a slight excess kurtosis. The first-order autocorrelation is 0.393, but the series is stationary, as shown by the p-value from Augmented Dickey-Fuller (ADF) test. On average, there are 203,736 job postings each month from 1,614 unique firms. This leads to an average of 124 job postings per firm per month, spread across all states in the U.S.

INSERT TABLE 1 HERE

Figure 1 presents a plot of the monthly time series data for our Competition metric and the U.S. unemployment rate, spanning the period from January 2010 to December 2021. As the figure illustrates, our labor market competition metric captures market dynamics that are

[5]Alternatively, we set the threshold for the number of firm pairs based on the sample firms utilized in Hoberg and Phillips (2016), obtained from https://hobergphillips.tuck.dartmouth.edu/. We cross-reference the firms employed in their study with the 3-digit SIC code obtained from Compustat and determine the number of firms representing each industry. Using this count as the threshold for calculating average similarity for each firm in our own sample, we obtain qualitatively similar findings. These results are available upon request.

distinct from those captured by the unemployment indicator. Between 2010 and 2020, the unemployment rate declined while the labor market competitiveness fluctuated. However, during the first quarter of 2020, we observe a sudden jump in unemployment as businesses were forced to close due to the Covid-19 outbreak. This period was associated with a decrease in the overall labor market competition.

INSERT FIGURE 1 HERE

### *3.3. Stock market data*

Our stock data is obtained from the Center for Research in Security Prices (CRSP), which we access through the Wharton Research Data Services (WRDS). We collect daily data on closing price, volume, and market capitalization, and we link this data to the sample firms that we matched between the BGT dataset and Compustat. From the daily stock price data and market capitalization obtained from CRSP, we compute the equal- and value-weighted stock returns, average return correlation, and realized volatility on a monthly basis. We construct the monthly excess return as the difference between the return for the stock portfolio and the U.S. 1-month Treasury Bill.

### *3.4. Predictor variables*

Throughout the paper, we compare the predictive power of $Competition$ for aggregate excess returns with other forecasting variables which have been documented in the literature. We focus on predictor variables introduced in previous studies that are available at a monthly frequency. We group them into three categories: (1) stock market predictors, (2) labor market predictors, and (3) economic predictors. The full list of predictors, definitions, and sources is provided in Appendix B.

The first group, the stock market predictors, consists of the S&P500 returns, the CBOE Implied Volatility Index (VIX), the market average (return) correlation, the market realized volatility, the dividend-price ratio, and the dividend-earnings ratio. To ensure that our results are not influenced by serial correlation in returns, we use the S&P 500 returns in excess of the risk-free rate. The VIX measures investors' expectations of market volatility over the next 30 days and reflects the near-term market sentiment of the stock market. Whaley (2009) documents that the VIX works reasonably well as a predictor of expected stock index movements. Pollet and Wilson (2010) show that the stock returns average correlation and average variance predicts subsequent stock market excess returns. This positive relationship is due to higher aggregate risk reflected by the higher correlation between stocks. Dividend-price ratios and dividend-earnings ratios are known predictors of stock returns (see, e.g., Fama and French, 1988, Lettau and Ludvigson, 2001, Chen and Zhang, 2011).

The second group, labor market predictors, includes the average number of job postings, the employment growth rate, the unemployment rate, and economic policy uncertainty. According to Kothari and O'Doherty (2023), one of the most robust predictors of stock returns is the ratio of job postings to employment levels. They found that higher ratios indicate greater adjustment costs, which can lead to lower expected excess stock market returns. Unfortunately, the specific job openings-to-employment ratio used in their study is not publicly available. To address this limitation, we constructed a similar measure by dividing the total number of job postings by the number of firms posting those jobs. This approach provides a comparable proxy for the Kothari and O'Doherty ratio and enables us to investigate the relationship between job postings and stock returns. The employment growth rate is a negative predictor of stock market returns due to hiring frictions (Chen and Zhang, 2011). Previous theoretical and empirical studies have also established a link between the unemployment rate and the aggregate expected returns (Ludvigson and Ng, 2007; Hall, 2017). High unemployment rates are commonly associated with a high discount rate, which prompts investors to demand higher returns on their investments. Furthermore, economic policy uncertainty can significantly impact the labor market, as it may lead firms to withhold hiring, thereby exacerbating unemployment levels (Baker et al., 2016).

The economic predictors' group includes various indicators, including the Chicago Fed National Activity Index, Industrial Production Growth, NBER business cycle, term spread, and default spread. In their study, Fama and French (1989) observed that expected returns include risk premiums that move inversely with business conditions. Consequently, stock returns tend to decrease (increase) following periods of economic expansion (contraction). Based on this, we can anticipate a negative correlation between market fundamentals such as the Chicago Fed National Activity Index and Industrial Production Growth, while a positive correlation with NBER business cycle indicators suggests recessionary periods. Finally, the relationship between term spread and stock returns, as well as between the default yield spread, can be explained by risk factors, as has been well documented in various studies (see, e.g., Campbell, 1987; Fama, 1990; Vassalou and Xing, 2004).

As shown in Table 1, the average excess return from our equal-weighted stock market portfolio is approximately 1.36% per month (16.3% per annum) during the sample period from 2010 to 2021. This is primarily driven by the large stocks, where the average monthly return is 1.47%, while small stocks show an average monthly return of 0.65%. Contrary to the traditional convention, larger firms have yielded higher returns, particularly during the last two years from 2020 to 2021. For comparison, the Russell 1000 and Russell 2000 index returns are 0.87% and 0.74% per month, respectively.

The final column of Table 1 reports the correlations between our main measure of labor market competitiveness and the various predictors. The correlation coefficients indicate that our measure is not highly correlated with other predictors, ranging from -0.38 (with the term spread) to 0.18 (with the average job postings). The excess return of our market portfolio is highly correlated (0.95) with the excess return of the S&P 500, suggesting that our portfolio mimics the market very closely and is a good representation of the U.S. stock market.

## 4. Results

### *4.1. Validation tests*

To ensure that our labor market competitiveness measure accurately captures the intensity of labor demand, we conduct two validation tests. The first test examines the association between the labor market competitiveness metric and the labor market concentration index, which is derived in a similar fashion to the Herfindahl-Hirschman index (HHI). The second test investigates the association between the labor market competitiveness metric and the market average wage. We now discuss each of these validation tests in turn.

The HHI is a widely employed metric to assess market concentration in product markets. Recently, Azar et al. (2020) construct HHI for the labor market, recognizing that product and labor markets are distinct from each other. The HHI for market $m$ and month $t$ can be calculated as

$$HHI_{m,t} = \sum_{i=1}^{N} s_{i,m,t}^{2}, \tag{4}$$

where $s_{i,m,t}$ represents the market share of firm $i$ in market $m$ during month $t$. This market share is calculated as the sum of job postings by firm $i$ in a given month divided by the total job postings in the market during that same period. A high HHI suggests that the firm fills the market with a large number of job vacancies, thereby dominating the demand-side of the labor market. This is contrary to a competitive labor market scenario where multiple firms vie for a talent pool. As such, we anticipate a negative correlation between our measure of labor market competitiveness and the labor market HHI index.

Figure 2 presents the scatter plot between *Competition* and *HHI*. The correlation between the two metrics is negative. Greater labor market competitiveness is associated with lower labor market concentration. While the HHI may serve as an inverse indicator of labor market competitiveness, it is not an ideal proxy. The HHI gauges the participation rate of a firm in the labor market but does not take into account the overlap of job postings among firms in the market. As such, a firm may post many job vacancies, but only a few of these vacancies are also in demand by other firms. Our measure of competitiveness, on the other hand, is more nuanced than the HHI. We posit that considering the interconnectedness among firms is essential to better capture the true nature of competition in the labor market.

INSERT FIGURE 2 HERE

For the second validation test, we consider the market average of wages. Studies have documented that labor market concentration is associated with lower average wages. The Monopsony Theory proposes that as the labor market becomes more concentrated around fewer firms, job seekers will face diminished bargaining power, resulting in lower average wages (see, e.g., Boal and Ransom, 1997; Ashenfelter et al., 2010, among others). Consequently, we expect that higher labor market competitiveness to be positively correlated with the market average wage. To calculate the average wage, we utilize the salary information associated with each job posting in BGT. Wages are reported as a range rather than a single value. As such, we consider the average of the two values. We calculate the average wage for a given market and month by taking the simple average across all job postings from the firms in our sample.

Figure 3 shows that higher labor market competitiveness is associated with higher average wages. This implies that as more firms compete for a limited pool of resources, job seekers become more valuable. This is reflected in higher average salaries.

INSERT FIGURE 3 HERE

*4.2. Aggregate risk premium*

To assess the predictive power of labor market competitiveness for aggregate stock returns, we consider the realized future excess market returns. More specifically, we regress the future excess returns of the market portfolio on our measure of labor market competitiveness:

$$R_{t+1:t+h} = \alpha + \beta \cdot Competition_t + \varepsilon_{t+1:t+h}. \quad (5)$$

Here, $R_{t+1:t+h}$ is the cumulative excess return for the stock market portfolio from our sample over months $t+1$ through $t+h$, after subtracting the cumulative return on the one-month Treasury Bill. We consider h = 1, 3, 6, 9, 12, 15, and 18 months, representing the time horizons over which we calculate the future excess returns, spanning from one month to six quarters. To assist with the interpretation and economic significance of the predictability, we normalize the variable $Competition_t$. Specifically, from each month $t$ observation, we subtract the sample mean and divide this difference by the series standard deviation. The main coefficient of interest is $\beta$, as it captures the average response of market returns to competition in the labor market.

Table 2 reports the OLS estimates, the associated t-statistics, and the regression adjusted $R^2$ values. Panel A shows the result based on equal-weighted returns. The first set of columns shows that, for the market portfolio, the slope coefficient is negative and statistically significant. For instance, the coefficient for the first quarter ($h = 3$) is -0.022, suggesting that a one standard deviation increase in labor market competitiveness leads to a 2.2% decrease in stock excess return over the next quarter. The coefficients remain significant until the fourth quarter ($h = 12$), indicating that the stock market adjusts to changes in labor market competitiveness within less than a year.

INSERT TABLE 2 HERE

In the next two sets of columns, we consider portfolios constructed using the small and large firms in our sample, i.e., those with market capitalization lower and higher than the full sample median, respectively. We observe that return predictability is stronger for the small compared to the larger market portfolio, i.e., the magnitude of the competition coefficients is larger, and the predictability lasts longer, up until the fifth quarter ($h = 15$). We further examine the predictive power of labor market competitiveness on stock market indices, the Russell 2000 and Russell 1000, representing the smallest 2000 stocks and the largest 1000 stocks in the US, respectively. The results are consistent with those shown by our small and large market portfolios. This indicates that the predictive power of labor market competitiveness on stock returns is stronger for smaller firms compared to larger ones.

Panel B of Table 2 presents the results based on value-weighted returns. While the results show fewer significant coefficients, they are consistently negative across various time horizons. More importantly, the predictability is stronger for the small market portfolio and the Russell 2000 returns, indicating that smaller firms are more responsive to labor market competitiveness.

Next, we conduct pairwise horseraces in a multiple regression framework to compare the predictive power of labor market competitiveness with other known predictors of stock returns. We assess the incremental effects using the following multivariate regression specification,

$$R_{t+1:t+h} = \alpha + \gamma \cdot Predictor_t + \beta \cdot Competition_t + \varepsilon_{t+1:t+h}, \tag{6}$$

where $Predictor_t$ is one of the predictor variables discussed in Section 3.

Table 3 reports the results of the regression analyses based on the next quarter's equal-weighted stock returns ($h = 3$).[6] In Panel A, we employ each of the predictor variables separately in the predictive regressions. The second column presents the expected sign based

[6] Results based on value-weighted stock returns are reported in Appendix C.

on the findings in extant literature. Many of the known predictors are significant in predicting future stock excess returns in our regression model. For example, in terms of stock market predictors, we find the S&P 500 excess returns, VIX, average correlation, and realized volatility significantly predict stock returns over the next quarter. An increase in the VIX leads to a risk premium as investors expect higher compensation for holding riskier stocks. Similarly, average correlation leads to higher returns as it reflects an increase in aggregate risk (Pollet and Wilson, 2010). In terms of labor market predictors, log(average posts), unemployment rate, and economic policy uncertainty are significant factors affecting stock returns. Additionally, the NBER business cycle and the default spread are significant economic predictors.

INSERT TABLE 3 HERE

In Panel B of Table 3, we include labor market competitiveness in the regression model. The coefficients for labor market competitiveness remain negative and highly significant, with Newey-West t-statistics above 2.0 and, in many cases, over 3.0 in absolute terms. The coefficients range from -0.016 (in the model with the unemployment rate) to -0.027 (in the model with term spread and economic policy uncertainty), indicating that increased competition leads to lower stock returns by 1.6% to 2.7% over the next quarter. More importantly, our finding suggests that the explanatory power of labor market competitiveness for aggregate market returns is unaffected by the presence of other predictors. The adjusted $R^2$ is larger after the inclusion of our competitiveness measure (an average of 0.072 in Panel A and 0.118 in Panel B), suggesting that the competition metric contributes to the power of the predictive model. Our findings strongly support our first hypothesis that increased labor market competitiveness has a significant impact on stock returns.

In Panels C and D, we estimate Eq. (6) for the portfolios of small and large stocks, respectively. The coefficients for labor market competitiveness are significantly negative in both panels. However, the magnitude is noticeably larger for the small stock portfolio. This observation further shows that small firms are more affected by the level of competition in the labor markets.

Table 4 presents the results for the regression analyses based on a longer horizon, i.e., over the next four quarters.[7] Consistent with the previous results, labor market competitiveness remains predictive of market excess returns. Except for the model with the Unemployment rate, the coefficient for labor market competitiveness is negative and statistically significant in predicting stock returns. The coefficients range from -0.018 (unemployment rate) to -0.055 (term spread), implying that an increase in labor market competition leads to a lower return from 1.8% to 5.5% over the next 12 months. Splitting the sample into small and large market portfolios, we again observe that the negative predictive power of labor market competitiveness on stock returns is stronger for the portfolio consisting of small stocks.

INSERT TABLE 4 HERE

*4.3. Transmission channel*

Why does labor market competitiveness serve as a predictor of aggregate market returns? In the preceding section, we argue that heightened labor market competitiveness can result in increased stock correlation, thereby eroding the benefits of diversification (risk channel). Conversely, intensified labor market competition can also prompt companies to allocate additional resources toward attracting new workers and retaining high-performing employees (cash flow channel). Drawing from Campbell and Shiller (1988), unexpected asset returns can be decomposed into two components: shocks pertaining to cash flows, which reflect changes in firm fundamentals, and shocks related to discount rates, which indicate varying levels of risk aversion or investor sentiment over time. Our investigation aims to discern which

[7] Results based on value-weighted stock returns are reported in Appendix D.

of these channels predominantly influences the stock market's response to labor market competition.

We estimate the monthly cash flow and discount rate shocks using the return decomposition approach proposed by Campbell and Shiller (1988). The model decomposes the unexpected stock returns into shocks about future dividends, which reflect changes in firm fundamentals, and future discount rates, which indicate varying levels of risk aversion or investor sentiment over time:

$$r_{t+1} - E_t r_{t+1} = (E_{t+1} - E_t)\sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t)\sum_{j=0}^{\infty} \rho^j r_{t+1+j}$$

$$= N_{CF,t+1} - N_{DR,t+1}, \tag{7}$$

where $r_{t+1}$ is a log stock return, $E_t$ and $E_{t+1}$ are expectations at time $t$ and $t+1$, $\Delta d_{t+1}$ is a one-period change in log dividends, $\rho$ is a constant discount factor, $N_{CF,t+1}$ is shocks about future cash flows, and $N_{DR,t+1}$ is shocks about future discount rates. To implement this decomposition, we follow Campbell and Vuolteenaho (2004) and estimate the series of cash flow and discount rate shocks using a first-order vector autoregression (VAR) model, which captures the linear interdependencies among the time series:

$$z_{t+1} = c + \Gamma z_t + u_{t+1} \tag{8}$$

where $z_{t+1}$ is an m-by-1 state vector with $r_{t+1}$ as its first element, $c$ and $\Gamma$ are m-by-1 vectors and m-by-m matrix of constant parameters, and $u_{t+1}$ is an i.i.d. m-by-1 vector of shocks. Subsequently, the cash flow and discount rate shocks are linear functions of the shock vector:

$$N_{CF,t+1} = (e1' + e1'\lambda)u_{t+1}$$

$$N_{DR,t+1} = e1'\lambda u_{t+1} \tag{9}$$

where $\lambda \equiv \rho\Gamma(I - \rho\Gamma)^{-1}$, and $e1$ is a vector whose first element is equal to one and zero otherwise. $\rho$ is a constant close to but lower than 1.[8] Following Campbell and Vuolteenaho (2004), we employ these four state variables: (1) the excess market return, (2) the term spread, (3) the market's smoothed price-earnings ratio (measured as the log ratio of the S&P500 price index to a ten-year moving average of S&P 500 earnings), and (4) the small-stock value spread (measured as the difference between the log book-to-market ratios of small value and small growth stocks).[9]

Once we have obtained the time series of the cash flow shocks ($N_{CF,t+1}$), and discount rate shocks ($N_{DR,t+1}$), we regress each series on the lagged labor market competitiveness variable, i.e., $Competition_t$, to examine how these shocks respond to changes in labor market competitiveness. The results of these regressions are reported in Table 5.

INSERT TABLE 5 HERE

Panel A shows that cash flow shocks respond negatively to a one standard deviation increase in the competition variable. The coefficient estimate is -0.005 for the market portfolio, -0.008 for the small market portfolio, -0.003 for the large market portfolio, -0.005 for the Russell 2000 index, and -0.004 for the Russell 1000 index. Apart from the large market portfolio, all the above coefficients are significant at the 10% level or better. The discount rate shocks, on the other hand, are not responsive to labor market competition as none of the coefficients are statistically significant. These findings suggest that the expected cash flows decrease in response to an increase in labor market competitiveness.

One concern regarding the above approach is that the results may be sensitive to the choice of state variables in the VAR (Chen and Zhao, 2009). Since the true model is unknown,

[8] Campbell and Vuolteenaho (2004) recommend a $\rho$ of $0.95^{\frac{1}{12}}$ for monthly data as it corresponds to an annual average dividend-price or consumption-wealth ratio of 5.2 percent, which is reasonable for a long-term investor.
[9] Data on the term spread and smoothed price-earnings ratio are obtained from Robert Shiller's online repository. The small-stock value spread is constructed using the size and book-to-market sorted portfolio data from Kenneth French's website.

discount rate shocks cannot be perfectly measured. Inevitably, the cash flow shocks, which are obtained as the residuals, inherit the misspecification error of the discount rate shocks. To alleviate this concern, we employ an alternative set of state variables that have been employed in various studies, such as Petkova (2006) and Atilgan, Bali, and Demirtas (2015). In particular, we employ the following five state variables: (1) the excess market return, (2) the term spread, (3) dividend yield, (4) credit default spread, and (5) stochastically detrended risk-free rate (measured as the yield on the one-month Treasury bill minus its one-year backward moving average).

Panel B presents the findings from an alternative VAR model. The analysis reveals a negative impact of labor market competitiveness on cash flow shocks. The coefficient estimates consistently demonstrate negative effects across all portfolios, except for the large market portfolio, where the significance is not statistically significant. Nonetheless, these results align with our previous findings, indicating that an increase in labor market competitiveness leads to a decrease in expected cash flows.

A decrease in cash flow can be driven by multiple factors, and our proposition suggests that intensified labor market competition drives firms to allocate more resources toward hiring new employees or retaining high-caliber talent. This prompts us to investigate whether labor market competitiveness corresponds to an upsurge in firms' expenditures, as this would provide further evidence of firms allocating more resources to compete for talent. Specifically, we analyze firms' SGA expenses as a proxy for workforce expenses and firms' R&D spending, which often aligns with salaries for skilled employees. Additionally, we evaluate the level of cash holding, recognizing its significance in gauging firms' ability to generate revenue.

We perform a panel regression analysis at a firm-year level, i.e., we regress firm expenditure on the labor market competitiveness as follows:

$$Y_{i,k} = c + \beta_1 \cdot Competition_k + \Gamma \cdot Controls_{i,k} + \varepsilon_{i,k}, \quad (10)$$

$$Y_{i,k} = c + \beta_1 \cdot Competition_k + \beta_2 \cdot Small_{i,k} + \beta_3 \cdot Competition_k \times Small_{i,k} + \Gamma \cdot Controls_{i,k} + \varepsilon_{i,k}. \tag{11}$$

where $Y_{i,k}$ is either the log of SGA expenses, R&D expenditure, or cash holding for firm *i* in year $k$. Our study focuses on firms for which these accounting fundamentals are available in December each year when the majority of companies release such information. We construct $Competition_k$ as the past 12-month average labor market competitiveness three months prior to December, i.e., from October year *k-1* to September year *k*. This approach allows us to assess the predictive power of labor market competitiveness on firms' expenses in the next quarter. Additionally, we consider alternative averages of 6 and 9 months prior to December to ensure robustness. In Eq. (11), we introduce $Small_{i,k}$ as an indicator variable if the market capitalization of firm *i* is lower than the sample median. We interact $Competition_k$ and $Small_{i,k}$ to test our proposition that small firms are more likely to be adversely influenced by labor market competitiveness. The control variables, $Controls_{i,k}$, include firm market capitalization (*Size*), leverage ratio (*Leverage*), return on assets (*ROA*), Tobin's Q ratio (*TQ*), and (log) capital expenditure (*Capex*) in December of year *k*. To address potential biases, we apply firm fixed-effect and cluster the standard error by firm and year.

In Panel A of Table 6, we present the findings regarding the predictive power of labor market competitiveness on firm expenditures for the subsequent quarter. The first column reveals that higher competition leads to increased firms' SGA expenses, consistent with our earlier finding that the increased expenditure acts as a negative shock to cash flow. We also find that higher competition leads to higher R&D expenditure in the second column, suggesting increased compensation for R&D personnel. Additionally, we find a decrease in cash holdings following an increase in labor market competitiveness. The last three columns further show that smaller firms are more significantly impacted by the increase in labor market competition, as evidenced by the significant coefficients for the interaction term. The coefficients for the control variables corroborate previous literature (see, e.g., Hirshleifer et al., 2012, Huang et al., 2019). In particular, larger firms tend to have higher expenses and cash holdings. More leveraged firms have lower cash reserves. Firms with higher ROA tend to have lower expenses and higher cash. Finally, firms with high capital expenditure tend to also have larger SGA and R&D expenses.

INSERT TABLE 6 HERE

Panels B and C present the results on the predictive power of labor market competitiveness on firms’ expenses and cash holdings for the subsequent two and three quarters. The findings remain consistent with the previous panel, as higher competition continues to correlate with increased SGA and R&D expenditures. This trend is stronger for the smaller firms, although the significance of the interaction term coefficient in the fifth column of Panel C diminishes. Notably, we observe that cash holdings for smaller firms decrease following intensified labor market competition, but this effect becomes significant only after the second quarter. This is evidenced by the significant negative coefficients for the interaction term in the last column of Panels B and C.

In summary, our findings indicate that heightened labor market competitiveness has a detrimental impact on cash flows, as reflected by negative shocks to firms' cash flows due to increased expenditures. This is manifested in increased expenses, specifically in terms of selling, general and administrative, and research and development expenditures, which serve as proxies for personnel-related costs. Additionally, our results highlight that higher expenditures are associated with decreased cash holdings for firms, with smaller firms being particularly vulnerable to this effect.

### *4.4. Is labor market competitiveness priced?*

Our previous evidence suggests that stronger labor market competition leads to lower stock returns. For our next analysis, we explore whether a stock's expected return is related to the sensitivity of its return to movements in labor market competitiveness, referred to as its 'competition beta.' Arguably, stocks that are more sensitive to labor market competition have more variable returns compared to stocks that are less sensitive. This suggests that stocks with high competition beta are riskier relative to stocks with low competition beta. Therefore, they should command higher expected returns. Based on this, we should observe that a strategy exploiting competition beta generates positive and significant excess returns.

Our analysis covers all common stocks traded on the NYSE, NYSE MKT, and NASDAQ. All data is collected from CRSP (exchange codes 1, 2, and 3, and share codes 10 and 11). We exclude stocks with prices below \$5 and above \$1,000. For each stock, we estimate its historical competition beta by regressing stock excess returns on *Competition* using the most recent five years of monthly data. To ensure more precise estimates of beta, we require firms to have 60 monthly observations. Based on these filters, we ended up with 2,859 unique stocks over the period from 2010 to 2022.

We adopt a regression specification similar to the one used by Pástor and Stambaugh (2003),

$$r_{i,t} = c + \beta_i^{Comp} \cdot Competition_t + \beta_i^{MKT} \cdot MKT_t + \beta_i^{SMB} \cdot SMB_t + \beta_i^{HML} \cdot HML_t + \epsilon_{i,t}. \tag{11}$$

$r_{i,t}$ denotes stock $i$'s excess return in month $t$, $MKT$, $SMB$, and $HML$, represent the market risk premium, the size factor, and the value factor, respectively, as defined by Fama and French (1993). Of particular interest is the coefficient $\beta_i^{Comp}$, which captures the stock's sensitivity to labor market competitiveness. Given our focus on this sensitivity, we take the absolute value of $\beta_i^{Comp}$ to isolate its magnitude regardless of the direction of the relationship.

Building upon our previous findings that labor market competitiveness has a more significant impact on portfolios of small stocks compared to large stocks, we also take into account the cross-sectional variation across firms. More specifically, at the end of each year, we sort stocks into five size quintiles based on their market capitalization. Within each size quintile, we further sort stocks based on their (absolute) competition betas. By doing so, we create 5×5 distinct portfolios. To track the performance of these portfolios, we calculate the returns over the next 12 months across multiple years, forming a single return series for each of the 25 portfolios. To examine the return premium associated with competition beta, we also form a high-minus-low portfolio that takes a long position in the portfolio of stocks with high competition beta and a short position in the portfolio of stocks with low competition beta, and we calculate the returns on this portfolio.

Table 7 presents the results of the portfolio sorting. Panel A corresponds to the small stocks (size quintile 1), while Panel E corresponds to the large stocks (size quintile 5). Within each panel, the stocks are further split into those with low competition beta (beta quintile 1) up to those with high competition beta (beta quintile 5).[10]

INSERT TABLE 7 HERE

The table shows that competition betas serve as a predictor of future stock returns, particularly for the smaller firms, i.e., those with an average market capitalization of $140 million. Panel A, in particular, shows that the average competition beta ranges from 0.17 for Q1 to 4.12 for Q5. The monthly excess returns are lowest for Q1 (1.22%) and highest for Q5

[10] Results based on value-weighted stock returns are reported in Appendix E.

(2.74%). More importantly, the high-minus-low (Q5-Q1) portfolio provides an excess return of 1.52% per month (18% per annum) with a t-statistic of 2.01. The Sharpe ratio ranges from 0.21 for Q1 to 0.28 for Q5, and that of the Q5-Q1 portfolio is 0.23. We do not observe such a pattern across the other size quintiles.

These findings suggest that labor market competitiveness possesses a significant predictive ability for stock returns, particularly for small firms. In our subsequent analysis, we will direct our attention toward the competition beta premium, specifically within the small stock portfolios.

Next, we perform formal asset pricing regressions to assess the extent to which the variation in the average returns of the competition beta-sorted portfolios can be explained by existing risk factors. We conduct regression analysis on the excess returns of our portfolios, incorporating various risk factors commonly used in empirical asset pricing studies, including the Fama-French (1993) three-factor model, the Carhart (1997) four-factor model, the Fama-French (2015) five-factor model, and the Hou, Xue, and Zhang (2015) q-factor model. The alpha derived from this analysis represents the portion of a portfolio's expected returns that cannot be explained by its exposure to the risk factors included in the model.

Table 8 reports the alphas from existing risk factor models. Our findings across all five beta quintiles indicate that the cross-sectional return spread across portfolios sorted on competition beta cannot be explained by other known risk factors. More importantly, the alphas in the long-short portfolio (Q5-Q1) remain statistically significant, indicating that the positive risk premium that we document cannot be simply attributed to common risk factors.[11]

INSERT TABLE 8 HERE

[11] Results based on value-weighted stock returns are reported in Appendix F.

Overall, our evidence strongly supports the hypothesis that labor market competitiveness exerts a more pronounced impact on smaller firms. The presence of a positive risk premium suggests that stocks with higher sensitivity to competition beta exhibit higher expected returns. This outcome aligns with our second hypothesis that, compared to larger firms, smaller firms face greater challenges in hiring workers under competitive market conditions.

## 6. Conclusion

This study contributes to the existing literature by introducing a novel measure of labor market competitiveness, which captures the intensity of demand for specific occupations. This measure provides a more nuanced understanding of labor market dynamics, as it recognizes that competitiveness can increase even without a rise in total hiring. This approach offers a significant departure from previous studies that primarily rely on the total number of hires as a proxy for labor market competitiveness.

Our empirical analysis reveals a significant negative relationship between labor market competitiveness and future aggregate stock returns, even after controlling for other known predictors. This finding underscores the importance of labor market conditions in influencing stock market performance. We also find that heightened labor market competition leads to negative cash flow shocks, reflected in increased firm expenditures and decreased cash holdings. These effects are particularly pronounced for smaller firms, which often have less bargaining power in the labor market. Furthermore, our results provide evidence of a risk premium associated with labor market competitiveness. Specifically, smaller firms with higher sensitivity to labor market competition tend to yield higher returns, suggesting that investors require compensation for the increased risk associated with these stocks.

Overall, our study provides evidence that heightened competition in the labor market has detrimental impacts on firms' future stock returns. Our study also highlights the significant role of labor market competitiveness in shaping stock market returns and firm financial performance. Our findings emphasize the need for investors and firms’ management to pay close attention to labor market dynamics when making decisions.

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## Appendix A. Sample firm distribution across various industry sectors

This table compares the industry distribution of matched firms in our dataset to the universe of firms in Compustat. Firms are grouped into 16 two-digit NAICS industries. *job_postings* is the number of high-skilled jobs posts, *firms_BGT* and *firms_BGT(%)* are the number of unique firms in our dataset and their relative percentage, respectively. *firms_COMP* and *firms_COMP(%)* are the number of unique firms from Compustat and its relative percentage. *%Difference* is the difference between *firms_BGT(%)* and *firms_COMP(%)*.

| *Sector* | *job_postings* | *firms_BGT* | *firms_BGT(%)* | *firms_COMP* | *firms_COMP(%)* | *%Difference* |
|---|---|---|---|---|---|---|
| Mining & Logging | 203,271 | 131 | 3.0% | 283 | 3.2% | -0.27% |
| Construction | 150,116 | 59 | 1.3% | 74 | 0.8% | 0.49% |
| Durable Goods | 4,147,838 | 925 | 20.9% | 1,479 | 16.9% | 4.05% |
| Non-Durable Goods | 2,299,077 | 849 | 19.2% | 1,615 | 18.4% | 0.78% |
| Wholesale Trade | 633,340 | 103 | 2.3% | 144 | 1.6% | 0.69% |
| Retail Trade | 4,076,496 | 164 | 3.7% | 265 | 3.0% | 0.69% |
| Trans, Ware, and Util | 793,330 | 136 | 3.1% | 292 | 3.3% | -0.26% |
| Information | 1,782,929 | 552 | 12.5% | 1,054 | 12.0% | 0.46% |
| Finance and Insurance | 4,334,532 | 799 | 18.1% | 2,441 | 27.8% | -9.78% |
| Real Estate & Rental | 1,259,580 | 247 | 5.6% | 391 | 4.5% | 1.13% |
| Prof & Business | 2,028,090 | 229 | 5.2% | 354 | 4.0% | 1.14% |
| Educational Services | 83,234 | 21 | 0.5% | 46 | 0.5% | -0.05% |
| Health Care & Soc Assist | 1,687,078 | 83 | 1.9% | 136 | 1.6% | 0.33% |
| Arts, Ent, & Rec | 128,524 | 27 | 0.6% | 51 | 0.6% | 0.03% |
| Acco & Food | 2,586,489 | 83 | 1.9% | 118 | 1.3% | 0.53% |
| Other Services | 43,895 | 13 | 0.3% | 22 | 0.3% | 0.04% |
| Total | 26,237,819 | 4,421 | 100.0% | 8,765 | 100.0% | 0.00% |

Appendix B. Predictor variables

*B.1. Stock market predictors*

- **S&P 500 returns:** the monthly (end-of-month) returns of the Standard and Poor's 500 Composite Index. Source: Refinitiv Datastream.
- **Implied volatility:** the average daily value of the CBOE VIX index within the month. Source: Refinitiv Datastream.
- **Average correlation:** the average return correlation for the stocks in our matched sample. First, we compute the return correlation between each pair of firms $i$ and $j$ for each month $t$, $\rho_{i,j,t}$, using daily stock price data. We then calculate the equal-weighted average correlation as $Correl_t = \frac{1}{C(N,2)} \cdot \sum_{i=1}^{N} \sum_{j \neq i} \rho_{i,j,t}$.
- **Realized volatility:** the square root of the sum of squared daily returns of the stocks in our sample. Source: Compustat.
- **Dividend-price ratio:** the difference between the log of dividends paid on the S&P500 index and the log of the index level. Dividends are measured as a sum over the prior 12 months. Source: Amit Goyal online data repository.
- **Dividend-earnings ratio:** the difference between the log of earnings on the S&P 500 index and the log of the index level. Both dividends and earnings are measured as sums over the prior 12 months. Source: Amit Goyal online data repository.

*B.2. Labor market predictors*

- **Average job postings:** The average number of jobs posted per month per firm (includes parent company and subsidiaries). Source: Burning Glass.

- **Employment growth rate:** the log growth rate of seasonally adjusted total nonfarm payrolls of all employees over the prior three months. Source: The U.S. Bureau of Labor Statistics.
- **Unemployment rate:** the seasonally adjusted civilian unemployment rate. Source: The U.S. Bureau of Labor Statistics.
- **Economic Policy Uncertainty:** the monthly economic policy uncertainty index from Baker, Bloom, and Davis (2016). Source: https://www.policyuncertainty.com/

*B.3. Economic predictors*

- **Chicago Fed National Activity Index:** the monthly index designed to gauge overall economic activity and related inflationary pressure. Source: The Chicago Fed.
- **Industrial Production Growth:** the monthly percentage change in the volume of output generated by industrial sectors such as mining, manufacturing, energy, and public utilities. Source: Refinitiv Datastream.
- **NBER business cycle:** month indicators of peaks and troughs that frame economic recessions and expansions. Source: NBER.
- **Term spread:** the difference between the long-term Treasury bond yield and the Treasury Bill yield. Source: Amit Goyal online data repository.
- **Default spread:** the difference between the yield on Moody's Baa-rated corporate bonds and the yield on Moody's AAA-rated corporate bonds. Source: Amit Goyal online data repository.

## Appendix C. Multivariate regression results based on value-weighted next quarter returns

This table reports the multivariate regression results of value-weighted stock market excess returns on labor market competitiveness and other predictors. We use $Ret_{(t+1:t+3)}$ as the dependent variable. Panel A reports the results based on a univariate regression on known predictors (*Predictor*). Panel B reports the coefficients for *Competition* in addition to other known predictors. Panels C and D report the coefficients for *Competition* from the multivariate regressions based on small and large market portfolio returns, respectively. *sign* is the expected relation between predictor and stock returns (based on the literature). The sample period is from January 2010 to December 2021. Details on each of these variables can be found in Appendix B. Figures in parentheses are the Newey-West t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

| Dependent: $Ret_{(t+1:t+3)}$ | | Panel A: Univariate regression | | | Panel B: Multivariate regression | | | | | Panel C: Portfolio small | | Panel D: Portfolio large | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *sign* | *Predictor* | *t-stat* | *Adj.* $R^2$ | *Predictor* | *t-stat* | *Competition* | *t-stat* | *Adj.* $R^2$ | *Competition* | *t-stat* | *Competition* | *t-stat* |
| ***Stock market predictors*** | | | | | | | | | | | | | |
| *S&P500 Excess Return* | - | -0.299** | (-2.46) | 0.026 | -0.278** | (-2.33) | -0.009* | (-1.92) | 0.039 | -0.001*** | (-3.71) | -0.009* | (-1.88) |
| *VIX* | + | 0.005*** | (6.60) | 0.268 | 0.005*** | (6.77) | -0.010** | (-2.09) | 0.288 | -0.002*** | (-4.27) | -0.009** | (-2.05) |
| *Average Correlation* | + | 0.200*** | (2.86) | 0.110 | 0.195*** | (2.91) | -0.009** | (-2.14) | 0.122 | -0.001*** | (-4.42) | -0.008** | (-2.10) |
| *Realized Volatility* | + | 0.956*** | (6.72) | 0.169 | 0.961*** | (6.91) | -0.011** | (-2.39) | 0.190 | -0.002*** | (-4.18) | -0.010** | (-2.33) |
| *Dividend-Price Ratio* | + | 0.066 | (0.77) | 0.004 | 0.046 | (0.54) | -0.009* | (-1.93) | 0.016 | -0.001*** | (-3.52) | -0.008* | (-1.87) |
| *Dividend-Earnings Ratio* | + | 0.057 | (1.14) | 0.022 | 0.060 | (1.18) | -0.011** | (-2.14) | 0.042 | -0.002*** | (-3.77) | -0.010** | (-2.12) |
| ***Labor market predictors*** | | | | | | | | | | | | | |
| *log(average posts)* | - | -0.042* | (-1.77) | 0.024 | -0.035 | (-1.39) | -0.008* | (-1.67) | 0.031 | -0.001*** | (-3.01) | -0.007* | (-1.69) |
| *Employment Growth Rate* | - | -0.593** | (-2.37) | 0.029 | -0.575** | (-2.32) | -0.010** | (-2.06) | 0.045 | -0.002*** | (-3.80) | -0.009** | (-2.03) |
| *Unemployment Rate* | + | 0.661* | (1.80) | 0.043 | 0.573 | (1.49) | -0.006 | (-1.46) | 0.045 | -0.001*** | (-3.53) | -0.006 | (-1.51) |
| *Economic Policy Uncertainty* | + | 0.042*** | (7.09) | 0.207 | 0.044*** | (7.62) | -0.014*** | (-3.22) | 0.245 | -0.002*** | (-4.30) | -0.012*** | (-3.13) |
| ***Economic predictors*** | | | | | | | | | | | | | |
| *Chicago Fed National Activity Index* | - | -0.003 | (-0.93) | -0.001 | -0.003 | (-0.85) | -0.010** | (-2.10) | 0.016 | -0.002*** | (-3.79) | -0.009** | (-2.08) |
| *Industrial Production Growth* | - | -0.346 | (-0.86) | -0.001 | -0.336 | (-0.86) | -0.010** | (-2.12) | 0.016 | -0.002*** | (-3.80) | -0.009** | (-2.10) |
| *NBER Business Cycle* | + | 0.153*** | (9.88) | 0.070 | 0.149*** | (9.66) | -0.009** | (-2.00) | 0.084 | -0.001*** | (-3.79) | -0.009** | (-1.98) |
| *Term Spread* | + | -0.601 | (-0.80) | 0.005 | -1.075 | (-1.30) | -0.015*** | (-2.60) | 0.045 | -0.001*** | (-3.22) | -0.014** | (-2.54) |
| *Default Spread* | + | 3.568** | (2.07) | 0.056 | 3.263* | (1.90) | -0.008* | (-1.70) | 0.062 | -0.001*** | (-4.33) | -0.007* | (-1.67) |

## Appendix D. Multivariate regression results based on value-weighted next-year returns

This table reports the multivariate regression results of value-weighted stock market excess returns on labor market competitiveness and other predictors. We use $Ret_{(t+1:t+12)}$ as the dependent variable. Panel A reports the results based on a univariate regression on known predictors (*Predictor*). Panel B reports the coefficients for *Competition* in addition to other known predictors. Panels C and D report the coefficients for *Competition* from the multivariate regressions based on small and large market portfolio returns, respectively. *sign* is the expected relation between predictor and stock returns (based on the literature). The sample period is from January 2010 to December 2021. Details on each of these variables can be found in Appendix B. Figures in parentheses are the Newey-West t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

| Dependent: $Ret_{(t+1:t+3)}$ | | Panel A: Univariate regression | | | Panel B: Multivariate regression | | | | | Panel C: Portfolio small | | Panel D: Portfolio large | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *sign* | *Predictor* | *t-stat* | *Adj. $R^2$* | *Predictor* | *t-stat* | *Competition* | *t-stat* | *Adj. $R^2$* | *Competition* | *t-stat* | *Competition* | *t-stat* |
| ***Stock market predictors*** | | | | | | | | | | | | | |
| *S&P500 Excess Return* | - | -0.477 | (-1.59) | 0.018 | -0.455 | (-1.50) | -0.011 | (-1.21) | 0.020 | -0.004*** | (-2.68) | -0.010 | (-1.11) |
| *VIX* | + | 0.011*** | (5.05) | 0.378 | 0.011*** | (5.06) | -0.013 | (-1.35) | 0.384 | -0.004*** | (-2.92) | -0.011 | (-1.23) |
| *Average Correlation* | + | 0.362*** | (2.80) | 0.112 | 0.356*** | (2.76) | -0.010 | (-1.18) | 0.113 | -0.003*** | (-2.94) | -0.009 | (-1.05) |
| *Realized Volatility* | + | 2.098*** | (6.29) | 0.260 | 2.106*** | (6.34) | -0.014 | (-1.55) | 0.269 | -0.004*** | (-2.93) | -0.012 | (-1.39) |
| *Dividend-Price Ratio* | + | 0.386 | (1.14) | 0.038 | 0.362 | (1.06) | -0.008 | (-0.92) | 0.035 | -0.003** | (-2.43) | -0.007 | (-0.78) |
| *Dividend-Earnings Ratio* | + | 0.174 | (1.58) | 0.073 | 0.178 | (1.61) | -0.015 | (-1.50) | 0.081 | -0.004*** | (-2.73) | -0.013 | (-1.37) |
| ***Labor market predictors*** | | | | | | | | | | | | | |
| *log(average posts)* | - | -0.111** | (-2.45) | 0.055 | -0.106** | (-2.26) | -0.007 | (-0.69) | 0.050 | -0.003** | (-2.11) | -0.006 | (-0.60) |
| *Employment Growth Rate* | - | -1.563** | (-2.16) | 0.071 | -1.550** | (-2.16) | -0.012 | (-1.32) | 0.074 | -0.004*** | (-2.72) | -0.011 | (-1.21) |
| *Unemployment Rate* | + | 1.795** | (2.15) | 0.109 | 1.784** | (2.01) | -0.001 | (-0.08) | 0.102 | -0.002* | (-1.80) | -0.001 | (-0.05) |
| *Economic Policy Uncertainty* | + | 0.114*** | (9.24) | 0.480 | 0.117*** | (10.57) | -0.022*** | (-3.49) | 0.511 | -0.004*** | (-3.15) | -0.019*** | (-3.02) |
| ***Economic predictors*** | | | | | | | | | | | | | |
| *Chicago Fed National Activity Index* | - | -0.009 | (-0.88) | 0.009 | -0.009 | (-0.86) | -0.012 | (-1.35) | 0.012 | -0.004*** | (-2.73) | -0.011 | (-1.23) |
| *Industrial Production Growth* | - | -0.702 | (-0.46) | -0.001 | -0.710 | (-0.47) | -0.013 | (-1.40) | 0.004 | -0.004*** | (-2.75) | -0.011 | (-1.28) |
| *NBER Business Cycle* | + | 0.403*** | (16.73) | 0.161 | 0.399*** | (16.48) | -0.010 | (-1.12) | 0.162 | -0.004*** | (-2.69) | -0.009 | (-1.03) |
| *Term Spread* | + | -2.410 | (-1.43) | 0.053 | -3.261* | (-1.76) | -0.028** | (-2.13) | 0.093 | -0.003* | (-1.94) | -0.024** | (-2.02) |
| *Default Spread* | + | 9.436*** | (2.84) | 0.118 | 9.210*** | (2.73) | -0.007 | (-0.77) | 0.114 | -0.003*** | (-3.48) | -0.006 | (-0.66) |

## Appendix E. Portfolio sorting (value-weighted returns)

This table reports the average returns for portfolios double-sorted by firm size, followed by (absolute) competition beta. Panel A shows the results for the small stocks (size Q1), and Panel E shows the results for the large stocks (size Q5). The sample period is from January 2015 to December 2022. We report the monthly value-weighted portfolio returns. We also present the Sharpe ratio, average competition beta, and the number of firms in each portfolio. Figures in parentheses are the Newey-West t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

| | Q1 | Q2 | Q3 | Q4 | Q5 | Q5-Q1 |
|---|---|---|---|---|---|---|
| **Panel A: Size Q1** | | | | | | |
| *Return* | 0.009 | 0.011** | 0.008 | 0.009 | 0.021** | 0.012** |
| *t-stat* | (1.57) | (2.21) | (1.42) | (1.47) | (2.19) | (2.08) |
| *Sharpe Ratio* | 0.14 | 0.20 | 0.13 | 0.14 | 0.24 | 0.23 |
| *Competition beta* | 0.17 | 0.53 | 0.96 | 1.67 | 4.12 | |
| *Average size (‘000)* | 137,369 | 141,836 | 145,348 | 135,776 | 132,271 | |
| *Firms* | 86 | 85 | 86 | 85 | 86 | |
| **Panel B: Size Q2** | | | | | | |
| *Return* | 0.011* | 0.010 | 0.010 | 0.013* | 0.011 | 0.000 |
| *t-stat* | (1.74) | (1.60) | (1.45) | (1.91) | (1.32) | (-0.01) |
| *Sharpe Ratio* | 0.15 | 0.14 | 0.12 | 0.18 | 0.12 | 0.00 |
| *Competition beta* | 0.17 | 0.50 | 0.91 | 1.52 | 3.34 | |
| *Average size (‘000)* | 609,573 | 611,072 | 626,050 | 603,955 | 583,260 | |
| *Firms* | 86 | 85 | 85 | 85 | 86 | |
| **Panel C: Size Q3** | | | | | | |
| *Return* | 0.010* | 0.008 | 0.010* | 0.011* | 0.008 | -0.001 |
| *t-stat* | (1.73) | (1.53) | (1.68) | (1.80) | (1.09) | (-0.33) |
| *Sharpe Ratio* | 0.14 | 0.13 | 0.14 | 0.15 | 0.10 | -0.04 |
| *Competition beta* | 0.17 | 0.48 | 0.84 | 1.36 | 2.93 | |
| *Average size (‘000)* | 1,760,266 | 1,750,317 | 1,759,275 | 1,734,632 | 1,704,006 | |
| *Firms* | 86 | 85 | 85 | 85 | 86 | |
| **Panel D: Size Q4** | | | | | | |
| *Return* | 0.009* | 0.009* | 0.007 | 0.009 | 0.008 | -0.001 |
| *t-stat* | (1.80) | (1.69) | (1.44) | (1.63) | (1.37) | (-0.56) |
| *Sharpe Ratio* | 0.14 | 0.14 | 0.11 | 0.13 | 0.11 | -0.05 |
| *Competition beta* | 0.13 | 0.41 | 0.72 | 1.16 | 2.30 | |
| *Average size (‘000)* | 4,981,108 | 4,956,824 | 5,018,690 | 5,062,311 | 4,771,297 | |
| *Firms* | 86 | 85 | 85 | 85 | 86 | |
| **Panel E: Size Q5** | | | | | | |
| *Return* | 0.009** | 0.012*** | 0.009** | 0.008* | 0.007 | -0.002 |
| *t-stat* | (2.31) | (3.23) | (2.19) | (1.94) | (1.47) | (-0.64) |
| *Sharpe Ratio* | 0.16 | 0.25 | 0.16 | 0.15 | 0.10 | -0.07 |
| *Competition beta* | 0.11 | 0.34 | 0.59 | 0.92 | 1.80 | |
| *Average size (‘000)* | 63,063,005 | 64,728,338 | 50,346,940 | 41,917,296 | 39,242,397 | |
| *Firms* | 86 | 85 | 86 | 85 | 86 | |

## Appendix F. Asset pricing factor tests (value-weighted returns)

This table reports the results from asset pricing factor tests for portfolios sorted on competition beta. The dependent variable is the value-weighted portfolio returns. In Panel A, we use Fama and French (1996) three factors (MKT, SMB, and HML). In Panel B, we use the Fama and French three factors and the Carhart (1997) momentum factor (UMD). In Panel C, we use Fama and French (2015) five factors (MKT, SMB, HML, RMW, and CMA). In Panel D, we use Hou, Xue, and Zhang (2015) q-factors (MKT, SMB, IA, and ROE). The sample period is from January 2015 to December 2022. All coefficients are monthly. Figures in parentheses are the Newey-West t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

| | Q1 | Q2 | Q3 | Q4 | Q5 | Q5-Q1 |
|---|---|---|---|---|---|---|
| Panel A: FF3 | | | | | | |
| *alpha* | 0.003* | 0.006*** | 0.003* | 0.002 | 0.013*** | 0.010** |
| | (1.80) | (3.75) | (1.81) | (1.01) | (3.18) | (2.31) |
| *MKT* | 0.007*** | 0.007*** | 0.008*** | 0.009*** | 0.011*** | 0.004*** |
| | (13.85) | (16.52) | (15.41) | (21.37) | (8.03) | (2.62) |
| *SMB* | 0.007*** | 0.007*** | 0.008*** | 0.009*** | 0.012*** | 0.005* |
| | (8.97) | (8.72) | (11.27) | (9.15) | (4.83) | (1.80) |
| *HML* | 0.004*** | 0.004*** | 0.004*** | 0.002*** | 0.002*** | -0.002** |
| | (5.40) | (5.71) | (6.70) | (4.11) | (2.92) | (-2.43) |
| Panel B: FF4 | | | | | | |
| *alpha* | 0.004** | 0.007*** | 0.004** | 0.003 | 0.012*** | 0.008** |
| | (2.29) | (4.18) | (2.21) | (1.25) | (3.44) | (2.10) |
| *MKT* | 0.007*** | 0.007*** | 0.007*** | 0.009*** | 0.012*** | 0.005*** |
| | (15.29) | (13.72) | (16.82) | (20.47) | (7.27) | (3.08) |
| *SMB* | 0.007*** | 0.006*** | 0.008*** | 0.008*** | 0.013*** | 0.006** |
| | (8.05) | (8.78) | (11.07) | (8.63) | (4.98) | (2.09) |
| *HML* | 0.003*** | 0.003*** | 0.003*** | 0.002*** | 0.003** | 0.000 |
| | (4.63) | (4.69) | (6.52) | (3.70) | (2.28) | (-0.37) |
| *UMD* | -0.002*** | -0.001* | -0.002** | -0.001 | 0.002 | 0.004 |
| | (-2.55) | (-1.68) | (-2.53) | (-1.53) | (0.97) | (1.52) |
| Panel C: FF5 | | | | | | |
| *alpha* | 0.003 | 0.006*** | 0.002 | 0.002 | 0.013*** | 0.010** |
| | (1.36) | (3.55) | (1.41) | (0.97) | (3.36) | (2.43) |
| *MKT* | 0.007*** | 0.007*** | 0.008*** | 0.009*** | 0.012*** | 0.005*** |
| | (12.37) | (15.46) | (13.97) | (21.58) | (7.99) | (3.01) |
| *SMB* | 0.008*** | 0.007*** | 0.008*** | 0.009*** | 0.011*** | 0.003 |
| | (12.01) | (9.02) | (9.96) | (10.27) | (4.51) | (1.14) |
| *HML* | 0.003*** | 0.004*** | 0.003*** | 0.002*** | 0.001 | -0.002 |
| | (3.85) | (5.38) | (3.98) | (2.86) | (0.92) | (-1.61) |
| *RMW* | 0.003** | 0.002* | 0.000 | 0.001 | -0.004* | -0.006*** |
| | (2.28) | (1.78) | (0.31) | (0.78) | (-1.68) | (-2.55) |
| *CMA* | -0.001 | -0.001 | 0.001 | 0.000 | 0.003 | 0.004 |
| | (-0.41) | (-1.21) | (1.40) | (-0.06) | (0.99) | (1.15) |
| Panel D: HXZ | | | | | | |
| *alpha* | 0.003 | 0.006** | 0.003 | 0.003 | 0.014*** | 0.011*** |
| | (1.41) | (2.49) | (1.42) | (1.04) | (3.86) | (2.75) |
| *MKT* | 0.008*** | 0.007** | 0.008*** | 0.009*** | 0.011*** | 0.003** |
| | (12.17) | (13.54) | (17.94) | (21.09) | (8.22) | (2.36) |
| *SMB* | 0.007*** | 0.007*** | 0.007*** | 0.008*** | 0.012*** | 0.005* |
| | (5.53) | (5.72) | (6.79) | (7.70) | (5.71) | (1.81) |
| *I/A* | 0.003*** | 0.002** | 0.004*** | 0.001* | 0.003 | 0.000 |
| | (3.17) | (2.22) | (4.70) | (1.73) | (1.51) | (0.00) |
| *ROE* | -0.002 | -0.001 | -0.003*** | -0.002*** | -0.004*** | -0.002 |
| | (-1.41) | (-1.38) | (-2.96) | (-3.29) | (-2.60) | (-1.07) |

Figure 1. Labor market competitiveness over time

This figure shows the time series of the monthly value of the labor market competitiveness (left axis) and the unemployment rate (right axis). The unemployment rate is collected from the U.S. Bureau of Labor Statistics. The sample period is from January 2020 to December 2021.

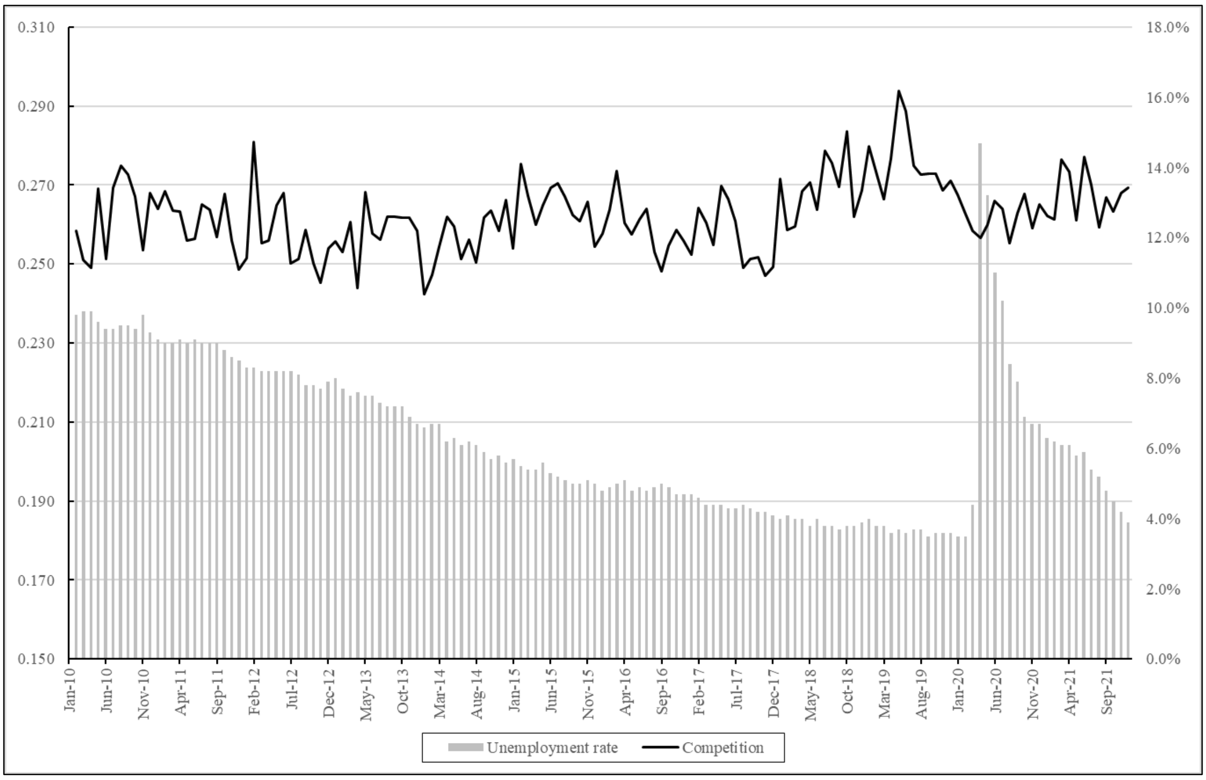


Figure 2. Labor market competition and labor market concentration index (HHI)

This figure shows the scatter plots between labor market competitiveness and the labor market concentration index (HHI). The sample period is from January 2020 to December 2021. Trendline is dashed.

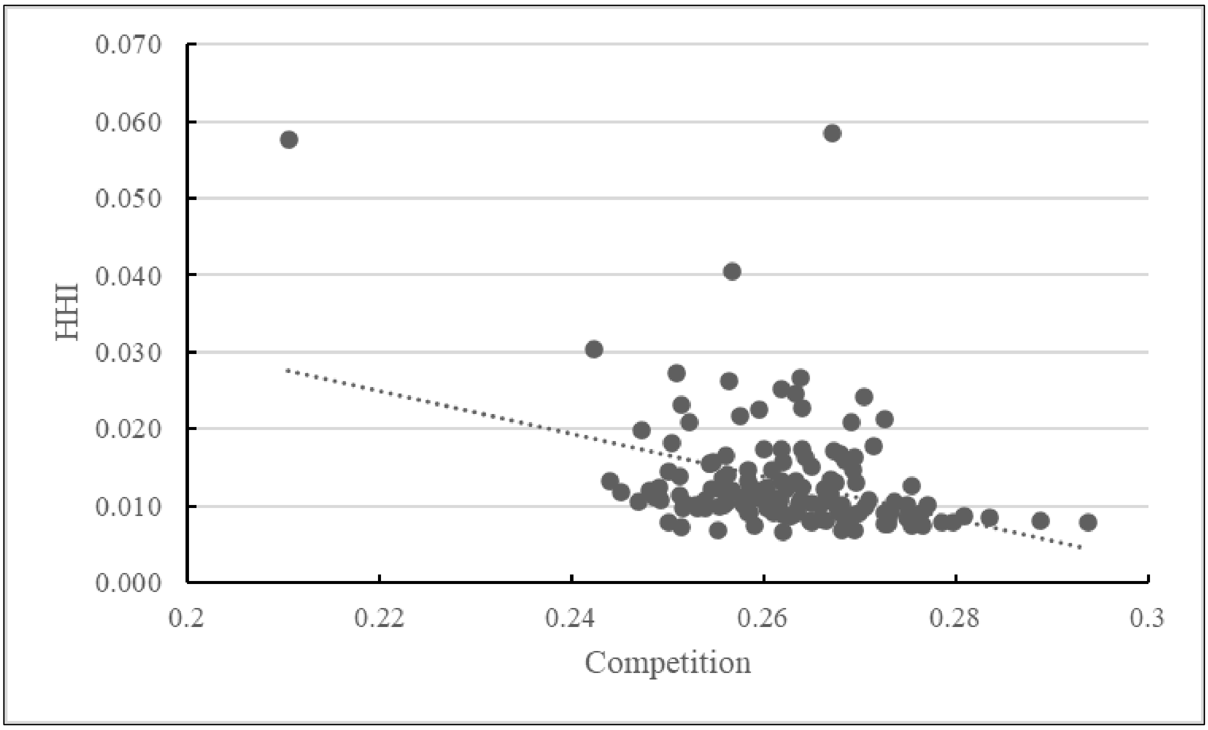
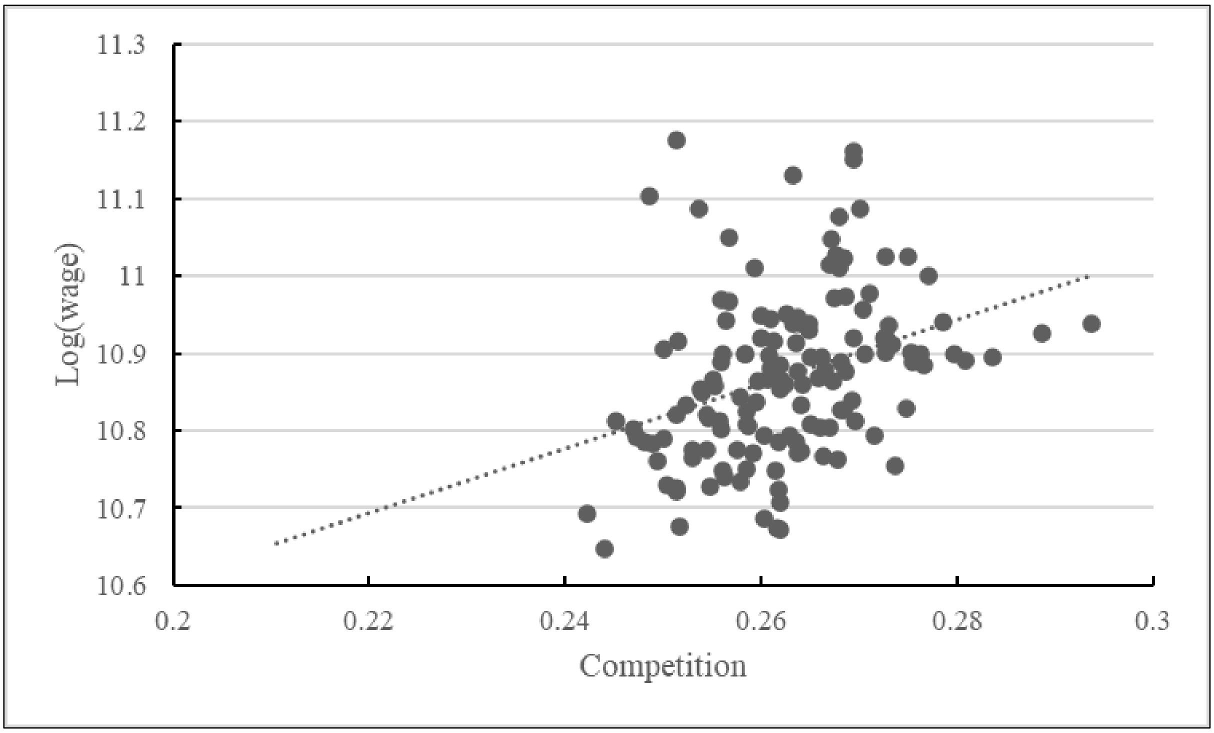


Figure 2. Labor market competition and market average wage

This figure shows the scatter plots between labor market competitiveness and the (log) market average wage. The sample period is from January 2020 to December 2021. Trendline is dashed.



## Table 1. Summary statistics

This table reports monthly summary statistics for the labor market competitiveness, portfolio returns, and other stock market return predictors. *ACF* is the first-order autocorrelation function, and *ADF* is the Augmented Dickey-Fuller test p-value. The sample period is from January 2010 to December 2021.

| *Variables* | *Mean* | *Median* | *Std. Dev.* | *Min* | *Max* | *Skew* | *Kurt* | *ACF* | *ADF* | *Correlation with Competition* |
|---|---|---|---|---|---|---|---|---|---|---|
| Labor market competitiveness (*Competition*) | 0.262 | 0.262 | 0.010 | 0.211 | 0.294 | -0.585 | 7.400 | 0.393 | 0.00 | 1.00 |
| Total job postings monthly | 203,736 | 213,780 | 69,964 | 15,188 | 389,605 | 0.029 | 2.753 | 0.816 | 0.00 | 0.38 |
| Unique firms monthly | 1,614 | 1,539 | 299 | 498 | 2105 | -0.107 | 3.022 | 0.915 | 0.00 | 0.58 |
| Average job postings | 124 | 123 | 31 | 30 | 202 | -0.030 | 2.499 | 0.734 | 0.06 | 0.18 |
| *Portfolio returns* | | | | | | | | | | |
| Portfolio market | 0.0136 | 0.0172 | 0.054 | -0.205 | 0.190 | -0.275 | 5.327 | -0.035 | 0.00 | 0.01 |
| Portfolio small | 0.0065 | 0.0090 | 0.054 | -0.163 | 0.174 | -0.255 | 3.730 | -0.046 | 0.00 | -0.03 |
| Portfolio large | 0.0147 | 0.0170 | 0.044 | -0.112 | 0.145 | -0.161 | 4.013 | -0.091 | 0.00 | 0.05 |
| Russell 2000 | 0.0074 | 0.0120 | 0.058 | -0.249 | 0.194 | -0.529 | 5.455 | -0.046 | 0.00 | 0.01 |
| Russell 1000 | 0.0087 | 0.0125 | 0.047 | -0.216 | 0.167 | -0.638 | 6.854 | -0.077 | 0.00 | 0.04 |
| *Stock market predictors* | | | | | | | | | | |
| S&P500 Excess Return | 0.011 | 0.017 | 0.040 | -0.133 | 0.120 | -0.530 | 4.199 | -0.110 | 0.00 | 0.09 |
| *VIX* | 18.498 | 16.585 | 6.963 | 9.510 | 53.540 | 1.888 | 7.898 | 0.690 | 0.00 | 0.00 |
| Average Correlation | 0.244 | 0.225 | 0.111 | 0.063 | 0.630 | 0.977 | 3.898 | 0.447 | 0.00 | -0.07 |
| Realized Volatility | 0.042 | 0.035 | 0.029 | 0.014 | 0.273 | 4.388 | 32.338 | 0.469 | 0.00 | 0.01 |
| Dividend-Price Ratio | -3.960 | -3.940 | 0.120 | -4.370 | -3.770 | -1.769 | 6.142 | 0.898 | 0.85 | -0.24 |
| Dividend-Earnings Ratio | -0.920 | -0.905 | 0.196 | -1.240 | -0.480 | 0.205 | 2.366 | 0.983 | 0.20 | 0.03 |
| *Labor market predictors* | | | | | | | | | | |
| Employment Growth Rate | 0.063 | 0.058 | 0.022 | 0.035 | 0.147 | 0.782 | 3.350 | 0.900 | 0.08 | -0.31 |
| Unemployment Rate | 0.003 | 0.004 | 0.021 | -0.154 | 0.064 | -5.368 | 40.032 | 0.597 | 0.00 | 0.04 |
| Economic Policy Uncertainty | 1.615 | 1.450 | 0.715 | 0.640 | 5.040 | 2.033 | 8.434 | 0.710 | 0.00 | 0.11 |
| *Economic predictors* | | | | | | | | | | |
| Chicago Fed National Activity Index | -0.051 | -0.010 | 1.728 | -17.960 | 6.120 | -7.417 | 83.151 | 0.084 | 0.00 | 0.05 |
| Industrial Production Growth | 0.001 | 0.002 | 0.014 | -0.132 | 0.063 | -4.967 | 54.081 | 0.189 | 0.00 | 0.01 |
| NBER Business Cycle | 0.014 | 0.000 | 0.117 | 0.000 | 1.000 | 8.307 | 70.014 | 0.493 | 0.00 | -0.05 |
| Term Spread | 0.021 | 0.020 | 0.012 | 0.000 | 0.040 | -0.102 | 2.094 | 0.928 | 0.17 | -0.38 |
| Default Spread | 0.025 | 0.026 | 0.005 | 0.017 | 0.036 | 0.125 | 2.046 | 0.931 | 0.10 | -0.20 |

# Table 2. Univariate regression results

This table reports the univariate regression results of stock market excess returns on the lagged labor market competitiveness. The dependent variable $Ret_{(t+1:t+h)}$ is the cumulative stock returns from month $t+1$ to month $t+h$, where $h = \{1, 3, 6, 9, 12, 15, 18\}$. Panels A and B report the results based on equal-weighted and value-weighted returns, respectively. *Portfolio market* is the returns of a portfolio constructed from the firms in our sample. *Portfolio small* is returns based on small stocks in the sample (lower than the size median). *Portfolio large* is returns based on large stocks in the sample (higher than the size median). *Russell 2000* is the returns of a portfolio from the smallest 2000 stocks in the Russell 3000 index. *Russell 1000* is the returns of a portfolio from the largest 1000 stocks in the Russell 3000 index. The sample period is from January 2010 to December 2021. Regression coefficients for the constant are not reported for brevity. Figures in parentheses are the Newey-West t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

| | | *Portfolio market* | | | *Portfolio small* | | | *Portfolio large* | | | *Russell 2000* | | | *Russell 1000* | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Obs | *Competition* | *t-stat* | *Adj. R2* | *Competition* | *t-stat* | *Adj. R2* | *Competition* | *t-stat* | *Adj. R2* | *Competition* | *t-stat* | *Adj. R2* | *Competition* | *t-stat* | *Adj. R2* |
| Panel A: Equal-weighted returns | | | | | | | | | | | | | | | | |
| *h=1* | 143 | 0.000 | (-0.03) | 0.00 | -0.007** | (-2.40) | 0.01 | -0.003 | (-1.25) | 0.00 | -0.005* | (-1.72) | 0.00 | -0.004 | (-1.44) | 0.00 |
| *h=3* | 141 | -0.022*** | (-3.25) | 0.05 | -0.027*** | (-3.83) | 0.08 | -0.015*** | (-2.74) | 0.04 | -0.022*** | (-2.83) | 0.04 | -0.016*** | (-2.82) | 0.04 |
| *h=6* | 138 | -0.023** | (-2.32) | 0.03 | -0.032*** | (-2.86) | 0.06 | -0.014* | (-1.73) | 0.01 | -0.027** | (-2.23) | 0.03 | -0.018** | (-1.96) | 0.03 |
| *h=9* | 135 | -0.040*** | (-3.10) | 0.06 | -0.054*** | (-3.68) | 0.12 | -0.027*** | (-2.84) | 0.05 | -0.051*** | (-3.15) | 0.09 | -0.036*** | (-2.95) | 0.09 |
| *h=12* | 132 | -0.038*** | (-2.63) | 0.04 | -0.057*** | (-3.49) | 0.10 | -0.025** | (-2.36) | 0.03 | -0.055*** | (-3.32) | 0.08 | -0.040*** | (-3.74) | 0.08 |
| *h=15* | 129 | -0.024 | (-1.19) | 0.01 | -0.048** | (-2.40) | 0.06 | -0.015 | (-0.98) | 0.00 | -0.045** | (-2.24) | 0.05 | -0.036*** | (-2.90) | 0.06 |
| *h=18* | 126 | 0.005 | (0.20) | -0.01 | -0.022 | (-0.87) | 0.01 | 0.007 | (0.33) | -0.01 | -0.017 | (-0.62) | 0.00 | -0.019 | (-1.13) | 0.01 |
| Panel B: Value-weighted returns | | | | | | | | | | | | | | | | |
| *h=1* | 143 | 0.000 | (0.06) | -0.01 | -0.001*** | (-4.13) | 0.05 | -0.002 | (-0.72) | -0.01 | -0.002 | (-0.56) | -0.01 | 0.000 | (0.08) | -0.01 |
| *h=3* | 141 | -0.010** | (-2.11) | 0.02 | -0.002*** | (-3.81) | 0.15 | -0.009** | (-2.09) | 0.02 | -0.019*** | (-2.62) | 0.04 | -0.010** | (-2.03) | 0.02 |
| *h=6* | 138 | -0.006 | (-0.86) | 0.00 | -0.002*** | (-2.81) | 0.11 | -0.005 | (-0.77) | 0.00 | -0.023** | (-2.02) | 0.03 | -0.008 | (-1.05) | 0.00 |
| *h=9* | 135 | -0.016** | (-2.04) | 0.02 | -0.003*** | (-3.07) | 0.14 | -0.014** | (-1.97) | 0.02 | -0.045*** | (-3.24) | 0.09 | -0.020** | (-2.52) | 0.04 |
| *h=12* | 132 | -0.013 | (-1.42) | 0.00 | -0.004*** | (-2.75) | 0.11 | -0.011 | (-1.27) | 0.00 | -0.050*** | (-3.77) | 0.09 | -0.021*** | (-2.95) | 0.04 |
| *h=15* | 129 | -0.002 | (-0.11) | -0.01 | -0.003** | (-2.07) | 0.07 | -0.001 | (-0.06) | -0.01 | -0.040*** | (-2.60) | 0.06 | -0.014 | (-1.44) | 0.01 |
| *h=18* | 126 | 0.019 | (1.04) | 0.01 | -0.002 | (-1.23) | 0.02 | -0.011 | (-1.27) | 0.00 | -0.017 | (-0.82) | 0.00 | 0.000 | (0.02) | -0.01 |

## Table 3. Multivariate regression results (next quarter returns)

This table reports the multivariate regression results of equal-weighted stock market excess returns on labor market competitiveness and other predictors. We use $Ret_{(t+1:t+3)}$ as the dependent variable. Panel A reports the results based on a univariate regression on known predictors (*Predictor*). Panel B reports the coefficients for *Competition* in addition to other known predictors. Panels C and D report the coefficients for *Competition* from the multivariate regressions based on small and large market portfolio returns, respectively. *sign* is the expected relation between predictor and stock returns (based on the literature). The sample period is from January 2010 to December 2021. Details on each of these variables can be found in Appendix B. Figures in parentheses are the Newey-West t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

| Dependent: $Ret_{(t+1:t+3)}$ | | Panel A: Univariate regression | | | Panel B: Multivariate regression | | | | | Panel C: Portfolio small | | Panel D: Portfolio large | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *sign* | *Predictor* | *t-stat* | *Adj. $R^2$* | *Predictor* | *t-stat* | *Competition* | *t-stat* | *Adj. $R^2$* | *Competition* | *t-stat* | *Competition* | *t-stat* |
| ***Stock market predictors*** | | | | | | | | | | | | | |
| *S&P500 Excess Return* | - | -0.330* | (-1.82) | 0.01 | -0.283 | (-1.61) | -0.021*** | (-3.14) | 0.06 | -0.026*** | (-3.73) | -0.014*** | (-2.55) |
| *VIX* | + | 0.007*** | (5.37) | 0.24 | 0.007*** | (5.47) | -0.022*** | (-3.65) | 0.30 | -0.027*** | (-4.29) | -0.015*** | (-2.86) |
| *Average Correlation* | + | 0.270*** | (2.65) | 0.10 | 0.257*** | (2.71) | -0.020*** | (-3.60) | 0.14 | -0.025*** | (-4.21) | -0.013*** | (-2.90) |
| *Realized Volatility* | + | 1.357*** | (6.31) | 0.17 | 1.366*** | (6.68) | -0.022*** | (-3.84) | 0.23 | -0.027*** | (-4.30) | -0.015*** | (-3.13) |
| *Dividend-Price Ratio* | + | 0.158 | (1.31) | 0.03 | 0.117 | (0.97) | -0.019*** | (-2.91) | 0.06 | -0.023*** | (-3.31) | -0.013** | (-2.36) |
| *Dividend-Earnings Ratio* | + | 0.107 | (1.43) | 0.04 | 0.113 | (1.49) | -0.023*** | (-3.23) | 0.10 | -0.028*** | (-3.82) | -0.015*** | (-2.72) |
| ***Labor market predictors*** | | | | | | | | | | | | | |
| *log(average posts)* | - | -0.087*** | (-3.02) | 0.06 | -0.072** | (-2.28) | -0.017*** | (-2.59) | 0.09 | -0.023*** | (-3.16) | -0.011** | (-2.10) |
| *Employment Growth Rate* | - | -0.501 | (-1.11) | 0.01 | -0.461 | (-1.05) | -0.022*** | (-3.26) | 0.05 | -0.027*** | (-3.83) | -0.015*** | (-2.72) |
| *Unemployment Rate* | + | 1.104** | (2.47) | 0.06 | 0.885* | (1.92) | -0.016*** | (-2.70) | 0.08 | -0.023*** | (-3.38) | -0.010** | (-2.10) |
| *Economic Policy Uncertainty* | + | 0.058*** | (5.04) | 0.19 | 0.062*** | (5.29) | -0.027*** | (-4.77) | 0.27 | -0.031*** | (-5.03) | -0.018*** | (-3.94) |
| ***Economic predictors*** | | | | | | | | | | | | | |
| *Chicago Fed National Activity Index* | - | -0.005 | (-1.40) | 0.00 | -0.005 | (-1.26) | -0.022*** | (-3.26) | 0.05 | -0.027*** | (-3.82) | -0.015*** | (-2.73) |
| *Industrial Production Growth* | - | -0.564 | (-0.98) | 0.00 | -0.543 | (-1.01) | -0.022*** | (-3.26) | 0.05 | -0.027*** | (-3.82) | -0.015*** | (-2.74) |
| *NBER Economic Cycle* | + | 0.228*** | (8.00) | 0.08 | 0.219*** | (7.70) | -0.021*** | (-3.21) | 0.12 | -0.026*** | (-3.79) | -0.014*** | (-2.65) |
| *Term Spread* | + | -0.303 | (-0.28) | -0.01 | -1.153 | (-1.01) | -0.027*** | (-3.32) | 0.06 | -0.031*** | (-3.73) | -0.019*** | (-2.77) |
| *Default Spread* | + | 6.086** | (2.52) | 0.08 | 5.381** | (2.30) | -0.017*** | (-2.97) | 0.11 | -0.023*** | (-3.62) | -0.011** | (-2.34) |

## Table 4. Multivariate regression results (next four-quarter returns)

This table reports the multivariate regression results of equal-weighted stock market excess returns on labor market competitiveness and other predictors. We use $Ret_{(t+1:t+12)}$ as the dependent variable. Panel A reports the results based on a univariate regression on known predictors (*Predictor*). Panel B reports the coefficients for *Competition* in addition to other known predictors. Panels C and D report the coefficients for *Competition* from the multivariate regressions based on small and large market portfolio returns, respectively. *sign* is the expected relation between predictor and stock returns (based on the literature). The sample period is from January 2010 to December 2021. Details on each of these variables can be found in Appendix B. Figures in parentheses are the Newey-West t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

| Dependent: $Ret_{(t+1:t+12)}$ | | Panel A: Univariate regression | | | Panel B: Multivariate regression | | | | | Panel C: Portfolio small | | Panel D: Portfolio large | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *sign* | *Predictor* | *t-stat* | *Adj. $R^2$* | *Predictor* | *t-stat* | *Competition* | *t-stat* | *Adj. $R^2$* | *Competition* | *t-stat* | *Competition* | *t-stat* |
| ***Stock market predictors*** | | | | | | | | | | | | | |
| *S&P500 Excess Return* | - | -0.641 | (-1.39) | 0.013 | -0.573 | (-1.23) | -0.036** | (-2.41) | 0.048 | -0.056*** | (-3.28) | -0.023** | (-2.14) |
| *VIX* | + | 0.015*** | (4.27) | 0.351 | 0.015*** | (4.33) | -0.037*** | (-2.74) | 0.391 | -0.057*** | (-3.61) | -0.024** | (-2.51) |
| *Average Correlation* | + | 0.544*** | (2.64) | 0.115 | 0.525*** | (2.59) | -0.034*** | (-2.62) | 0.146 | -0.054*** | (-3.70) | -0.022** | (-2.26) |
| *Realized Volatility* | + | 3.081*** | (5.30) | 0.254 | 3.104*** | (5.53) | -0.039*** | (-2.92) | 0.299 | -0.059*** | (-3.81) | -0.026*** | (-2.61) |
| *Dividend-Price Ratio* | + | 0.740 | (1.57) | 0.069 | 0.654 | (1.41) | -0.030** | (-2.17) | 0.089 | -0.045*** | (-3.07) | -0.018* | (-1.83) |
| *Dividend-Earnings Ratio* | + | 0.261 | (1.62) | 0.074 | 0.272* | (1.70) | -0.040*** | (-2.62) | 0.120 | -0.060*** | (-3.43) | -0.026** | (-2.36) |
| ***Labor market predictors*** | | | | | | | | | | | | | |
| *log(average posts)* | - | -0.160** | (-2.54) | 0.050 | -0.136** | (-2.15) | -0.030** | (-1.99) | 0.071 | -0.052*** | (-3.04) | -0.017 | (-1.63) |
| *Employment Growth Rate* | - | -2.407** | (-2.19) | 0.077 | -2.368** | (-2.19) | -0.037*** | (-2.58) | 0.113 | -0.056*** | (-3.45) | -0.024** | (-2.31) |
| *Unemployment Rate* | + | 3.095*** | (2.55) | 0.149 | 2.849** | (2.22) | -0.018 | (-1.33) | 0.153 | -0.039*** | (-2.61) | -0.009 | (-0.91) |
| *Economic Policy Uncertainty* | + | 0.153*** | (6.31) | 0.390 | 0.160*** | (7.82) | -0.051*** | (-4.55) | 0.468 | -0.068*** | (-4.63) | -0.034*** | (-4.28) |
| ***Economic predictors*** | | | | | | | | | | | | | |
| *Chicago Fed National Activity Index* | - | -0.014 | (-0.95) | 0.012 | -0.014 | (-0.91) | -0.037*** | (-2.59) | 0.049 | -0.057*** | (-3.47) | -0.024** | (-2.32) |
| *Industrial Production Growth* | - | -1.299 | (-0.58) | 0.003 | -1.322 | (-0.60) | -0.038*** | (-2.65) | 0.042 | -0.057*** | (-3.50) | -0.025** | (-2.37) |
| *NBER Business Cycle* | + | 0.629*** | (16.15) | 0.178 | 0.615*** | (15.76) | -0.034** | (-2.39) | 0.210 | -0.055*** | (-3.38) | -0.022** | (-2.10) |
| *Term Spread* | + | -2.083 | (-0.75) | 0.013 | -3.773 | (-1.33) | -0.055*** | (-2.75) | 0.089 | -0.066*** | (-3.28) | -0.036** | (-2.39) |
| *Default Spread* | + | 17.446*** | (3.74) | 0.187 | 16.547*** | (3.62) | -0.027** | (-2.43) | 0.203 | -0.044*** | (-4.32) | -0.017* | (-1.86) |

## Table 5. The impact of labor market competitiveness on cash flows and discount rate shocks

This table reports the regression results of cash flow shocks, $N_{CF,t+1}$, and discount rate shocks, $N_{DR,t+1}$, on labor market competitiveness, $Competition_t$. The cash flow and discount rate shocks used in Panel A are derived from a VAR using the following state variables: excess market returns, term spread, smoothened price-earnings ratio, and value spread. The shocks in Panel B are derived from a VAR using the following state variables: excess market returns, term spread, dividend yield, credit default spread, and detrended risk-free rate. The sample period is from January 2010 to December 2021. Figures in parentheses are the Newey-West t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

| | *Portfolio market* | | *Portfolio small* | | *Portfolio large* | | *Russell 2000* | | *Russell 1000* | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $N_{CF,t+1}$ | $N_{DR,t+1}$ | $N_{CF,t+1}$ | $N_{DR,t+1}$ | $N_{CF,t+1}$ | $N_{DR,t+1}$ | $N_{CF,t+1}$ | $N_{DR,t+1}$ | $N_{CF,t+1}$ | $N_{DR,t+1}$ |
| Panel A: VAR based on Campbell and Vuolteenaho (2004) | | | | | | | | | | |
| $Constant$ | 0.001 | 0.000 | 0.001 | 0.000 | 0.001 | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 |
| | (0.20) | (0.34) | (0.18) | (0.16) | (0.20) | (0.22) | (0.14) | (0.12) | (0.14) | (0.02) |
| $Competition_t$ | -0.005** | 0.000 | -0.008*** | -0.002 | -0.003 | 0.000 | -0.005** | -0.001 | -0.004* | -0.001 |
| | (-2.01) | (-0.38) | (-2.78) | (-1.13) | (-1.30) | (-0.24) | (-2.01) | (-1.21) | (-1.83) | (-1.26) |
| *Obs.* | 143 | 143 | 143 | 143 | 143 | 143 | 143 | 143 | 143 | 143 |
| *Adj.* $R^2$ | 0.004 | -0.006 | 0.018 | -0.002 | -0.002 | -0.007 | 0.003 | -0.001 | 0.003 | -0.001 |
| Panel B: VAR based on Atilgan et al. (2015) | | | | | | | | | | |
| $Constant$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (-0.01) | (0.00) | (-0.01) | (0.00) | (-0.01) | (0.00) | (-0.01) | (0.00) | (-0.01) | (0.00) |
| $Competition_t$ | -0.004** | 0.000 | -0.008*** | -0.003 | -0.004 | -0.002 | -0.003* | 0.001 | -0.006* | -0.003 |
| | (-2.36) | (0.04) | (-2.98) | (-0.65) | (-1.17) | (-0.34) | (-1.73) | (0.41) | (-1.67) | (-0.60) |
| *Obs.* | 143 | 143 | 143 | 143 | 143 | 143 | 143 | 143 | 143 | 143 |
| *Adj.* $R^2$ | 0.004 | -0.007 | 0.013 | -0.006 | 0.001 | -0.007 | 0.000 | -0.007 | 0.010 | -0.005 |

## Table 6. The impact of labor market competitiveness on firm cash flows

This table presents the panel regression results of firms' selling, general and administrative expenses (*SGA*), R&D expenses (*R&D*), and cash holding (*Cash*) on labor market competitiveness (*Competition*). All dependent variables are in natural log form. In Panels A, B, and C, *Competition* is lagged by 3-, 6- and 9-month from the dependent variable, respectively. *Small* is an indicator variable for firms whose market capitalization is below the sample median. The control variables include firm market capitalization (*Size*), leverage ratio (*Leverage*), return on assets (*ROA*), Tobin's Q ratio (*TQ*), and (log) capital expenditure (*Capex*). All dependent and explanatory variables are winsorized at the 1% level each tail. We include firm-fixed effect. Standard errors are clustered by firm and year. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

| VARIABLES | [1] R&D | [2] SGA | [3] Cash | [4] R&D | [5] SGA | [6] Cash |
|---|---|---|---|---|---|---|
| Panel A: *Competition* is lagged by 3-month | | | | | | |
| *Competition* | 3.871*** | 4.772*** | -6.043** | 3.047*** | 2.401** | -4.876 |
| | (3.36) | (3.39) | (-2.19) | (3.12) | (2.06) | (-1.62) |
| *Small* | | | | -0.525*** | -1.127*** | 0.736 |
| | | | | (-2.73) | (-2.83) | (1.31) |
| *Competition*Small* | | | | 1.724*** | 3.820*** | -2.362 |
| | | | | (2.33) | (2.45) | (-1.11) |
| *Size* | 0.562*** | 0.562*** | 0.749*** | 0.551*** | 0.545*** | 0.766*** |
| | (31.92) | (23.89) | (16.89) | (31.31) | (21.29) | (17.43) |
| *Leverage* | 0.016 | -0.033 | -0.188*** | 0.013 | -0.038* | -0.184*** |
| | (1.68) | (-1.60) | (-7.25) | (1.36) | (-1.84) | (-7.12) |
| *ROA* | -0.106*** | -0.126*** | 0.026** | -0.104*** | -0.124*** | 0.024* |
| | (-14.96) | (-8.82) | (2.13) | (-14.85) | (-8.75) | (1.96) |
| *TQ* | 0.000 | 0.002 | 0.004** | 0.000 | 0.001 | 0.004*** |
| | (0.58) | (1.79) | (3.14) | (0.45) | (1.67) | (3.20) |
| *Capex* | 0.048*** | 0.087*** | 0.007 | 0.048*** | 0.087*** | 0.007 |
| | (12.53) | (10.45) | (0.59) | (12.52) | (10.39) | (0.58) |
| *Constant* | -0.437 | -1.750*** | 0.453 | -0.112 | -0.943** | -0.023 |
| | (-1.40) | (-4.26) | (0.57) | (-0.40) | (-2.70) | (-0.03) |
| *Firm FE* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Obs.* | 37,010 | 18,125 | 43,198 | 37,010 | 18,125 | 43,198 |
| *Adj.* $R^2$ | 0.561 | 0.351 | 0.192 | 0.562 | 0.352 | 0.193 |
| Panel B: *Competition* is lagged by 6-month | | | | | | |
| *Competition* | 3.714*** | 4.696*** | -2.206 | 2.895** | 2.706** | -0.216 |
| | (2.97) | (3.12) | (-0.56) | (2.48) | (2.25) | (-0.05) |
| *Small* | | | | -0.501*** | -0.938** | 1.198** |
| | | | | (-3.30) | (-2.41) | (2.46) |
| *Competition*Small* | | | | 1.640*** | 3.113** | -4.125** |
| | | | | (2.81) | (2.03) | (-2.21) |
| Panel C: *Competition* is lagged by 9-month | | | | | | |
| *Competition* | 3.072*** | 3.660** | 0.623 | 2.437** | 2.365** | 2.490 |
| | (2.83) | (2.50) | (0.16) | (2.23) | (2.25) | (0.59) |
| *Small* | | | | -0.385*** | -0.628* | 1.102*** |
| | | | | (-2.88) | (-1.82) | (2.71) |
| *Competition*Small* | | | | 1.199** | 1.934 | -3.754** |
| | | | | (2.40) | (1.41) | (-2.44) |

# Table 7. Portfolio sorting

This table reports the average returns for portfolios double-sorted by firm size, followed by (absolute) competition beta. Panel A shows the results for the small stocks (size Q1), and Panel E shows the results for the large stocks (size Q5). The sample period is from January 2015 to December 2022. We report the monthly equal-weighted portfolio returns. We also present the Sharpe ratio, average competition beta, average market capitalization, and the number of firms in each portfolio. Figures in parentheses are the Newey-West t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

| | Q1 | Q2 | Q3 | Q4 | Q5 | Q5-Q1 |
|---|---|---|---|---|---|---|
| **Panel A: Size Q1** | | | | | | |
| *Return* | 0.012** | 0.014*** | 0.010* | 0.016** | 0.027** | 0.015** |
| *t-stat* | (2.25) | (2.63) | (1.75) | (2.36) | (2.35) | (2.01) |
| *Sharpe Ratio* | 0.21 | 0.25 | 0.17 | 0.24 | 0.28 | 0.23 |
| *Competition beta* | 0.17 | 0.53 | 0.96 | 1.67 | 4.12 | |
| *Average size (‘000)* | 137,369 | 141,836 | 145,348 | 135,776 | 132,271 | |
| *Firms* | 86 | 85 | 86 | 85 | 86 | |
| **Panel B: Size Q2** | | | | | | |
| *Return* | 0.011* | 0.010* | 0.011* | 0.012* | 0.010 | -0.001 |
| *t-stat* | (1.76) | (1.67) | (1.69) | (1.81) | 1.22 | -0.16 |
| *Sharpe Ratio* | 0.16 | 0.15 | 0.15 | 0.17 | 0.11 | -0.02 |
| *Competition beta* | 0.17 | 0.50 | 0.91 | 1.52 | 3.34 | |
| *Average size (‘000)* | 609,573 | 611,072 | 626,050 | 603,955 | 583,260 | |
| *Firms* | 86 | 85 | 85 | 85 | 86 | |
| **Panel C: Size Q3** | | | | | | |
| *Return* | 0.010* | 0.009 | 0.010 | 0.010* | 0.010 | 0.000 |
| *t-stat* | (1.82) | 1.58 | 1.60 | (1.76) | 1.16 | -0.07 |
| *Sharpe Ratio* | 0.15 | 0.13 | 0.13 | 0.14 | 0.11 | -0.01 |
| *Competition beta* | 0.17 | 0.48 | 0.84 | 1.36 | 2.93 | |
| *Average size (‘000)* | 1,760,266 | 1,750,317 | 1,759,275 | 1,734,632 | 1,704,006 | |
| *Firms* | 86 | 85 | 85 | 85 | 86 | |
| **Panel D: Size Q4** | | | | | | |
| *Return* | 0.009* | 0.008 | 0.007 | 0.009* | 0.008 | -0.001 |
| *t-stat* | (1.77) | 1.56 | 1.40 | (1.69) | 1.38 | -0.52 |
| *Sharpe Ratio* | 0.14 | 0.13 | 0.11 | 0.13 | 0.11 | -0.05 |
| *Competition beta* | 0.13 | 0.41 | 0.72 | 1.16 | 2.30 | |
| *Average size (‘000)* | 4,981,108 | 4,956,824 | 5,018,690 | 5,062,311 | 4,771,297 | |
| *Firms* | 86 | 85 | 85 | 85 | 86 | |
| **Panel E: Size Q5** | | | | | | |
| *Return* | 0.008** | 0.010*** | 0.011*** | 0.008* | 0.009* | 0.000 |
| *t-stat* | (2.14) | (2.63) | (2.69) | (1.93) | (1.88) | 0.22 |
| *Sharpe Ratio* | 0.16 | 0.19 | 0.20 | 0.14 | 0.14 | 0.02 |
| *Competition beta* | 0.11 | 0.34 | 0.59 | 0.92 | 1.80 | |
| *Average size (‘000)* | 63,063,005 | 64,728,338 | 50,346,940 | 41,917,296 | 39,242,397 | |
| *Firms* | 86 | 85 | 86 | 85 | 86 | |

## Table 8. Asset pricing factor tests

This table reports the results from asset pricing factor tests for portfolios sorted on competition beta. In Panel A, we use Fama and French (1996) three factors (MKT, SMB, and HML). In Panel B, we use the Fama and French three factors and the Carhart (1997) momentum factor (UMD). In Panel C, we use Fama and French (2015) five factors (MKT, SMB, HML, RMW, and CMA). In Panel D, we use Hou, Xue, and Zhang (2015) q-factors (MKT, SMB, IA, and ROE). The sample period is from January 2015 to December 2022. All coefficients are monthly. Figures in parentheses are the Newey-West t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

| | Q1 | Q2 | Q3 | Q4 | Q5 | Q5-Q1 |
|---|---|---|---|---|---|---|
| **Panel A: FF3** | | | | | | |
| *alpha* | 0.007*** | 0.009*** | 0.004*** | 0.009*** | 0.020*** | 0.014** |
| | (3.88) | (5.78) | (2.86) | (3.42) | (3.09) | (2.14) |
| *MKT* | 0.008*** | 0.007*** | 0.008*** | 0.009*** | 0.010*** | 0.003* |
| | (9.35) | (15.07) | (17.58) | (13.56) | (6.56) | (1.77) |
| *SMB* | 0.007*** | 0.008*** | 0.007*** | 0.008*** | 0.015*** | 0.009* |
| | (8.54) | (10.22) | (9.67) | (9.51) | (3.21) | (1.71) |
| *HML* | 0.003*** | 0.003*** | 0.003*** | 0.002*** | 0.001 | -0.002** |
| | (5.10) | (4.98) | (4.70) | (3.58) | (1.43) | (-2.31) |
| **Panel B: FF4** | | | | | | |
| *alpha* | 0.007*** | 0.009*** | 0.005*** | 0.009*** | 0.018*** | 0.011** |
| | (4.12) | (5.97) | (3.31) | (3.79) | (3.38) | (2.04) |
| *MKT* | 0.007*** | 0.006*** | 0.007*** | 0.009*** | 0.011*** | 0.004*** |
| | (8.74) | (12.95) | (16.59) | (11.89) | (7.92) | (3.37) |
| *SMB* | 0.006*** | 0.007*** | 0.007*** | 0.008*** | 0.016*** | 0.010* |
| | (8.30) | (10.09) | (9.04) | (9.24) | (3.02) | (1.76) |
| *HML* | 0.003*** | 0.003*** | 0.002*** | 0.002*** | 0.002* | 0.000 |
| | (4.12) | (4.08) | (4.14) | (3.12) | (1.71) | (-0.34) |
| *UMD* | -0.001*** | -0.001 | -0.002*** | -0.001 | 0.004 | 0.005 |
| | (-2.40) | (-1.34) | (-2.77) | (-1.50) | (1.11) | (1.41) |
| **Panel C: FF5** | | | | | | |
| *alpha* | 0.006*** | 0.009*** | 0.004*** | 0.009*** | 0.020*** | 0.015** |
| | (3.29) | (5.83) | (2.78) | (3.59) | (3.47) | (2.52) |
| *MKT* | 0.007*** | 0.006*** | 0.008*** | 0.009*** | 0.012*** | 0.005*** |
| | (10.78) | (16.54) | (15.67) | (13.40) | (8.54) | (3.80) |
| *SMB* | 0.008*** | 0.008*** | 0.008*** | 0.009*** | 0.013*** | 0.005 |
| | (8.66) | (9.08) | (8.55) | (9.32) | (3.24) | (1.30) |
| *HML* | 0.003*** | 0.004*** | 0.003*** | 0.002** | -0.001 | -0.004 |
| | (2.82) | (4.33) | (3.01) | (2.20) | (-0.35) | (-1.49) |
| *RMW* | 0.003** | 0.000 | 0.000 | 0.000 | -0.007** | -0.010*** |
| | (2.39) | (0.49) | (0.13) | (0.46) | (-2.48) | (-3.54) |
| *CMA* | 0.000 | -0.001 | 0.001 | 0.000 | 0.008 | 0.008 |
| | (-0.08) | (-1.08) | (0.44) | (0.00) | (1.22) | (1.23) |
| **Panel D: HXZ** | | | | | | |
| *alpha* | 0.006*** | 0.009*** | 0.005*** | 0.009*** | 0.021*** | 0.015*** |
| | (3.29) | (4.58) | (2.63) | (3.67) | (3.93) | (2.75) |
| *MKT* | 0.008*** | 0.007*** | 0.008*** | 0.009*** | 0.010*** | 0.002 |
| | (8.97) | (12.74) | (20.10) | (12.77) | (7.44) | (1.62) |
| *SMB* | 0.007*** | 0.008*** | 0.006*** | 0.008*** | 0.015*** | 0.008 |
| | (5.23) | (6.42) | (6.11) | (7.08) | (3.01) | (1.41) |
| *I/A* | 0.003*** | 0.002* | 0.003*** | 0.001 | 0.004 | 0.001 |
| | (3.55) | (1.80) | (3.64) | (1.59) | (1.33) | (0.36) |
| *ROE* | -0.002* | -0.002*** | -0.003*** | -0.002*** | -0.005*** | -0.003 |
| | (-1.77) | (-2.81) | (-3.70) | (-2.57) | (-2.56) | (-1.33) |