Labor-Based Asset Pricing

Yukun Liu*　　Vladimir Smirnyagin†

University of Rochester　　University of Virginia

May 12, 2025

Abstract

Expected returns and future cash flows are linked to firms' labor search decisions. Using data on the near-universe of online job vacancy postings, we document that vacancy rates negatively predict returns and positively predict cash flows in the cross-section of firms and industries. Firm-specific labor market conditions play an important role in understanding asset prices, as these predictive relationships are stronger for firms operating in less favorable labor market environments. We build a general equilibrium, production-based asset pricing model with heterogeneous firms, search frictions, and idiosyncratic labor market conditions. The model, parameterized to fit the vacancy rate distribution, reproduces central U.S. business cycle and aggregate asset pricing moments, and accounts for our empirical findings.

Keywords: Search-and-Matching; Vacancy Posting Rate; Labor-Market Conditions; Return; Cash Flow

JEL: E44, G12, J63

*Simon Business School, University of Rochester, Rochester, NY 14627, U.S.A.

†Corresponding author: Department of Economics, University of Virginia, Charlottesville, VA 22903, U.S.A. Phone: +1 (434) 924 3177. Email: vladimir.smirnyagin@virginia.edu.

1 Introduction

Labor is a crucial, yet often overlooked, determinant of firm production and corporate valuation.[1] For many firms, employees represent their most valuable assets. The workforce functions as a dynamic form of technology, capable of adapting to evolving investment opportunities and shifting expectations. As with any capital budgeting decision, a firm's labor demand is inherently forward-looking and subject to temporal fluctuations. Consequently, when firms adjust their workforce, they do so by advertising vacancies in an effort to find suitable matches among potential employees. The intensity of firms' search efforts, along with prevailing labor market conditions, can offer meaningful insights into their expected returns and future cash flows.

We use micro-data on job vacancy postings to empirically study the link between firms' search effort, labor market conditions, future returns and cash flows, both in the cross-section and in the aggregate time series. The dataset covers nearly the entire universe of online vacancy postings in the U.S., allowing us to observe the complete job posting profile of each company and to construct firm-level measures of search effort and labor market conditions. We link each vacancy posting to the corresponding company's financial and accounting data and quantify search effort by the number of postings per firm. Each posting includes detailed information on the employer's name, job title, location, wage, and job requirements, such as skills, certifications, experience, and education. This information enables us to proxy for the firm-specific labor market conditions that companies face.

We find that firms' vacancy posting rates negatively predict returns and positively predict cash flows. The predictive power of vacancy postings is stronger for firms operating under less favorable labor market conditions—such as those facing low relative labor market concentration, requiring high-skill workers, or operating in sectors with low vacancy filling rates. These results are consistent with a production-based asset pricing model with labor search frictions, whereby firms' search efforts respond to discount rates and expected cash flows.

We begin by illustrating the key empirical relationships in a partial-equilibrium static model of firms' labor search decisions. Firms in the model are heterogeneous with respect to idiosyncratic productivity and labor market conditions. When a firm's expected return is low or its expected

[1]The estimated labor share is substantial, ranging from 60 percent (Cooley and Prescott, 1995) to 75 percent (İmrohoroğlu and Tüzel, 2014).

cash flow is high, the present value of hiring an additional worker increases, leading the firm to post more vacancies. Consequently, vacancy postings should negatively predict future returns and positively predict future cash flows. Moreover, firms are constrained by the labor market conditions they face. When vacancies are relatively difficult to fill, or when labor market conditions are unfavorable, variations in vacancy posting rates become more informative about firms' expectations of returns and cash flows.

We assess these predictions both in the cross-section of firms and industries, as well as in the aggregate time series. In the cross-section of firms, search effort is strongly linked to expected returns. We find that firms with higher vacancy posting rates subsequently have lower stock returns. This result is robust to controls including employment growth, investment rates, and standard asset pricing factors such as size, book-to-market, and profitability. Similar findings emerge when we use industry-level data over a longer time period and when we use aggregate-level data spanning the past 70 years. Using several implied cost-of-capital measures as alternative proxies for expected returns, we confirm the negative relationship between vacancy posting rates and expected returns. Furthermore, vacancy posting rates negatively predict firms' corporate bond yields, suggesting a similar relationship for expected bond returns. On the cash flow side, consistent with the simple model's predictions, vacancy posting rates positively predict future cash flows and analyst-forecasted earnings, even after controlling for known cash flow predictors.

Subsequently, we study how labor market conditions affect both the expected return-vacancy and expected cash flow-vacancy relationships. We use three measures of firm-level labor market conditions: the firm's relative labor market concentration, its skill requirements, and the vacancy filling rate of the sector in which the firm operates. Consistent with the predictions of the illustrative model, both relationships are attenuated for firms operating in more favorable labor market environments. Specifically, the magnitude of the expected return–vacancy relationship declines by more than 50 percent among firms operating in above-median labor market conditions. Similarly, the expected cash flow-vacancy relationship weakens by more than 50 percent for such firms. These findings highlight the importance of labor market conditions in understanding asset prices.

Finally, we develop a general equilibrium, production-based asset pricing model with heterogeneous firms, in which firms post vacancies in order to hire workers. Firms are subject to both idiosyncratic productivity shocks and an aggregate TFP shock. The vacancy-filling rate is endogenous and depends on the number of unemployed workers and the aggregate mass of posted vacancies. In each period, firms may face unfavorable labor market conditions, which manifest as a vacancy-filling rate that is lower than the aggregate rate. The representative household consists of a unit mass of members, each of whom can be either employed or unemployed.[2] The household owns all firms and holds claims to their profits. Consequently, firms discount future payoffs using the household's stochastic discount factor.

We parameterize the model to match the mean, variance, and other distributional moments of the vacancy posting rate. In order to capture both standard business cycle statistics and aggregate asset pricing moments–such as the risk-free rate and the equity premium–we assume household preferences with external habit formation (Campbell and Cochrane, 1999; Jermann, 1998). Standard macroeconomic preferences typically cannot generate sufficient volatility in the stochastic discount factor and, as a consequence, fail to reproduce a realistic equity premium (e.g., Winberry, 2021).

The model accounts for our empirical findings. We show that the vacancy posting rate increases in idiosyncratic productivity. Furthermore, we show that even though firms are heterogeneous with respect to labor and productivity, it is productivity that predominantly accounts for cross-sectional differences in expected returns. Low-productivity firms are riskier and therefore command higher expected returns. As a result, in the model, higher vacancy rates are associated with lower expected returns and higher cash flows; this is consistent with the data.

The model also explains why the predictive power of vacancy rates varies with labor market conditions. In favorable environments, vacancy rates respond more elastically to changes in productivity. Consequently, a given difference in vacancy rates corresponds to a relatively small underlying productivity gap and, as a result, to smaller differences in expected returns and future cash flows. In contrast, under unfavorable labor market conditions, the same vacancy gap reflects a larger productivity gap, which amplifies return and cash flow differentials. Thus, the vacancy rate is a stronger predictor of firm outcomes when labor market conditions are unfavorable, in line with our empirical evidence.

This paper contributes to three strands of literature. First, it relates to the production-based

[2] For parsimony, we do not model flows into and out of the labor force, even though they have been shown to be as large as flows between unemployment and employment (Krusell, Mukoyama, Rogerson and Şahin, 2017).

asset pricing literature (Cochrane, 1991, 1996; Zhang, 2005). In particular, it builds on a growing body of research that explores the relationship between labor characteristics and asset prices. Chen, Kacperczyk and Ortiz-Molina (2011) and Favilukis and Lin (2015) study labor operating leverage induced by wage rigidity. Eisfeldt and Papanikolaou (2013) analyze the role of organizational capital in shaping firm risk. Belo, Lin and Bazdresch (2014) show that employment growth predicts stock returns in the cross-section and argue that workforce adjustments make firms less risky. Donangelo (2014) investigates labor mobility, while Donangelo, Gourio, Kehrig and Palacios (2018) focus on firms' labor shares. Kuehn, Simutin and Wang (2017) find that firms' exposure to aggregate labor market tightness negatively predicts stock returns. Zhang (2018) explores the asset pricing implications of routine-task labor. Belo, Donangelo, Lin and Luo (2018) show that aggregate hiring rates of public firms negatively predict future stock returns. Bai (2021) and Bai and Zhang (2022) show that labor search frictions can account for the aggregate credit spread puzzle and the aggregate stock market puzzle, respectively. In this paper, we directly study firms' labor search decisions and explore how labor demand, labor market conditions, and asset prices interact.

Second, this paper contributes to the macro-labor search-and-matching literature by exploring how search frictions interact with asset prices. The foundational search-and-matching models developed by Diamond (1982) and Mortensen and Pissarides (1994) emphasize the role of job postings and labor market conditions. More recently, Hall (2017) shows that the classic search-and-matching framework better matches unemployment data when the aggregate discount rate is aligned with that implied by the stock market's dividend-price ratio. Kehoe, Pastorino and Midrigan (2018) demonstrate that a labor market model incorporating time-varying risk premia arising from debt constraints helps explain regional unemployment dynamics in the aftermath of the financial crisis. Borovicka and Borovicková (2018) extract the equity market's stochastic discount factor and show that it fails to fully account for observed labor market fluctuations. In a related line of work, Petrosky-Nadeau, Zhang and Kuehn (2018) and Kilic and Wachter (2018) introduce time-varying rare disasters into a standard search-and-matching model to generate realistic unemployment volatility. In turn, Krusell, Mukoyama, Rogerson and Şahin (2020) argue that shocks to labor market frictions are needed to account for movements in the labor market. Luo and Tong (2024) show that variations in risk premia help explain the search intensity of unemployed workers.

Third, this paper is related to a growing body of research exploring the relationship between firms' economic environment and their economic as well as financial performance. Several studies investigate how geographic proximity and local economic conditions shape firm behavior. Dougal, Parsons and Titman (2015) find that firms' capital investment decisions are influenced by the investment behavior of nearby firms. Engelberg, Ozoguz and Wang (2018) show that firms' fundamentals tend to co-move within industry clusters. On the financial side, a number of papers explore the relationship between firm location and stock returns. Pirinsky and Wang (2006) document that stock returns of geographically proximate firms tend to co-move. Korniotis and Kumar (2013) show that local economic conditions help predict the returns of firms headquartered in the same area. Tuzel and Zhang (2017) find that firms located in areas with high local betas exhibit lower stock returns. Liu and Wu (2025) construct pairwise labor links using job posting data and demonstrate that a firm's labor market competitors often differ from its product market rivals.

The rest of the paper is organized as follows. Section 2 derives testable hypotheses from a static model. Section 3 discusses the data used in this paper. Section 4 reports main empirical results. We build a general equilibrium production-based asset pricing model with heterogeneous firms and local labor market conditions in Section 5. Section 6 concludes.

2 Illustrative Model

In this section, we derive testable hypotheses and illustrate the underlying mechanisms using a static model with search-and-matching frictions. In Section 5, we extend this framework to a general equilibrium, production-based asset pricing model with heterogeneous firms that operate subject to idiosyncratic productivity shocks, an aggregate TFP shock, and firm-specific labor market conditions. The qualitative predictions of the simple model carry over to our quantitative framework.

The model features two periods, 0 and 1, and a continuum of heterogeneous firms indexed by i. Labor is the sole input in production and is used to produce a perishable final good. Each firm chooses its workforce to maximize operating profits, defined as revenue less labor costs. Firms produce only in period 1, and the operating profits of firm i are given by $Zz_in_{i,1}$, where z_i denotes firm-specific productivity, Z is aggregate productivity, and $n_{i,1}$ is the number of workers employed by firm i in period 1. We assume that technology exhibits constant returns to scale in order to simplify derivations; we relax this assumption in our quantitative exercise in Section 5.

In the model, firms post vacancies and randomly get matched with workers. The vacancy-filling rate q_i captures firm i's idiosyncratic labor market conditions. All firms face a common labor separation rate s, and the wage w is exogenous, paid only in the final period.

Firm i is endowed with $n_{i,0}$ units of labor at time 0 and has a single opportunity to recruit additional workers in period 0. The firm posts $vc_{i,0}$ vacancies and incurs vacancy posting costs $\kappa \times vc_{i,0}$ as well as adjustment costs given by:

$$\frac{\varphi}{2}\left(\frac{vc_{i,0}}{n_{i,0}}\right)^2 n_{i,0},$$

where κ is the unit cost of vacancy posting and φ governs the degree of convex adjustment costs.

Each firm discounts future profits using its own firm-specific discount rate r_i, which varies across firms due to heterogeneous exposure to macroeconomic risk factors. Firm i chooses the number of vacancy postings to maximize its market value at the beginning of period 0:

$$\max_{vc_{i,0}}\left\{-\left[\kappa vc_{i,0}+\frac{\varphi}{2}\left(\frac{vc_{i,0}}{n_{i,0}}\right)^2 n_{i,0}\right]+\frac{1}{r_i}\left(Zz_i n_{i,1}-wn_{i,1}\right)\right\}$$

subject to the law of motion for labor:

$$n_{i,1}=(1-s)n_{i,0}+q_i vc_{i,0}.$$

The market value of firm i is the sum of the period 0 cash flow, $-\left[\kappa vc_{i,0}+\frac{\varphi}{2}\left(\frac{vc_{i,0}}{n_{i,0}}\right)^2 n_{i,0}\right]$, and the discounted value of period 1 cash flow, $Zz_i n_{i,1}-wn_{i,1}$. In this static model, the liquidation value of the workforce is normalized to zero. The firm faces a trade-off between incurring search costs in period 0 and generating operating profits in period 1. We assume z_i and Z are sufficiently large such that the firm posts a positive number of vacancies.

The first-order condition with respect to $vc_{i,0}$ yields:

$$\frac{vc^*_{i,0}}{n_{i,0}}=\frac{q_i(Zz_i-w)}{\varphi r_i}-\frac{\kappa}{\varphi}. \tag{1}$$

Firms choose the number of vacancies to post, taking r_i, q_i, Z, and z_i as given. The model yields a set of testable empirical predictions. Differentiating Equation (1) with respect to r_i gives

$$\frac{\partial\left(vc_{i,0}^{*}/n_{i,0}\right)}{\partial r_i}=-\frac{q_i\left(Zz_i-w\right)}{\varphi r_i^2}<0.$$

That is, if a firm has a lower expected return, it discounts future cash flows at a lower rate, thereby increasing the present value of hiring a worker. Consequently, the firm is willing to incur greater costs in searching for workers.

Prediction 1: The expected return is negatively related to the vacancy posting rate. That is, there is a negative expected return-vacancy relationship.

Similarly, differentiating Equation (1) with respect to z_i yields:

$$\frac{\partial\left(vc_{i,0}^{*}/n_{i,0}\right)}{\partial z_i}=\frac{q_i Z}{\varphi r_i}>0.$$

In other words, when firms anticipate higher future cash flows, the present value of hiring an additional worker rises, leading firms to be more willing to incur higher search costs.

Prediction 2: The expected cash flow is positively related to the vacancy posting rate. That is, there is a positive expected cash flow-vacancy relationship.

In order to investigate how firm-specific labor-market conditions affect the expected return-vacancy and the expected cash flow-vacancy relationships, we differentiate the absolute values of $\frac{\partial\left(vc_{i,0}^{*}/n_{i,0}\right)}{\partial r_i}$ and $\frac{\partial\left(vc_{i,0}^{*}/n_{i,0}\right)}{\partial z_i}$ with respect to q_i to obtain

$$\partial\left|\frac{\partial\left(vc_{i,0}^{*}/n_{i,0}\right)}{\partial r_i}\right|/\partial q_i=\frac{\left(Zz_i-w\right)}{\varphi r_i^2}>0$$

and

$$\partial\left|\frac{\partial\left(vc_{i,0}^{*}/n_{i,0}\right)}{\partial z_i}\right|/\partial q_i=\frac{Z}{\varphi r_i}>0.$$

With a higher q_i (i.e., under more favorable labor market conditions), vacancy rates are more sensitive to expected returns. Equivalently, the negative relationship between expected returns and vacancy postings becomes weaker. Similarly, the positive relationship between expected cash flows and vacancy postings is muted when q_i is high. Intuitively, if searching for workers is challenging but firms nonetheless invest effort into the search, this effort becomes more informative about their expectations regarding future returns and cash flows.

Prediction 3a: The negative expected return-vacancy relationship is weaker for firms with more favorable labor-market conditions.

Prediction 3b: The positive expected cash flow-vacancy relationship is weaker for firms with more favorable labor-market conditions.

Empirically, we would ideally test these relationships by regressing vacancy posting rates on expected returns or expected cash flows. However, we cannot directly observe expectations of returns and cash flows in the real world. If we regress vacancy posting rates on future returns or cash flows, we run into the classic error-in-variable problem leading to biased coefficient estimates. Therefore, we use the standard approach in asset pricing literature of regressing future returns or cash flows on current vacancy posting rates to achieve unbiased coefficient estimates:

$$x_{t+1} = a' + b' \times \frac{vc_t}{n_t} + \varepsilon'_{t+1},$$

where x_{t+1} is either realized future returns or cash flows.

3 Data

This section provides a detailed description of the vacancy posting data. We discuss how we construct measures of search effort, as well as measures of labor market conditions at the firm, industry, and aggregate levels. In addition, we summarize the financial data used in the analysis. Definitions of all variables are provided in Appendix B.

3.1 Firm-Level Data

Burning Glass Technologies. Burning Glass Technologies (BGT) is an analytics software company that provides real-time data on job vacancy postings. Each day, it scans more than 40,000 online job boards and company websites to collect postings. These postings are parsed, de-duplicated, and transformed into a machine-readable format, forming the basis for various labor market analytics products. The resulting database captures the near-universe of online job postings across all

U.S. metropolitan statistical areas (MSAs) for the years 2007 and 2010–2017, with 2017 being the last year of data for which we have access to.[3]

A key advantage of the BGT data is its broad coverage, which far exceeds that of databases based on a single source, such as CareerBuilder.com. This near-universe coverage is critical for our study, as it enables the construction of a complete job posting profile for each company. By contrast, the Job Openings and Labor Turnover Survey (JOLTS)–another widely used dataset–collects vacancy information from a representative sample of employers but is only available in aggregated form and lacks detail on job characteristics. In comparison, BGT provides over 70 standardized fields per posting, including detailed information on occupation, geography, skill requirements, and firm identifiers. Codified skill fields include educational and experience requirements, as well as thousands of specific skills extracted from the job description text. This rich information allows us to analyze a key, but often overlooked, margin of labor demand: skill requirements within occupations. Moreover, it facilitates firm-level analysis across different skill levels.

Despite its advantages, the BGT data has some limitations. Notably, it covers only online postings. While job ads have increasingly migrated online over time, there is still a concern that online postings may not fully represent all job openings. In the Appendix, we compare the industry distribution of BGT postings with that of JOLTS and find them largely comparable across most industries (Figure A.1). The BGT sample tends to under-represent the agricultural sector and over-represent the financial sector.

The BGT database includes information on occupations and, when available, employer names. However, employer names are missing in approximately 40 percent of the postings–primarily those listed on recruiting platforms that do not disclose employer identities. For our main analysis, we restrict the sample to postings that include employer names. A key step in our empirical analysis involves matching BGT postings to firms in the CRSP and Compustat databases. Since the only firm identifier in BGT is the employer name, we apply a combined machine-learning and manual matching procedure. Through this process, we match approximately 41 million vacancy postings to publicly traded firms listed on NYSE, Nasdaq, and AMEX. In our empirical analysis, we aggregate the data to the firm-quarter level.

[3]The database does not contain postings for years 2008 and 2009.

Vacancy Posting Rate. Our main variable of interest is the firm-level vacancy posting rate, defined as the number of vacancy postings scaled by the firm's total assets from the previous quarter (sourced from Compustat). For robustness, we also compute the vacancy rate scaled by the number of employees, using the most recent Compustat data. For industry- and aggregate-level analyses, we scale postings by total employment. In order to measure new information contained in vacancy posting behavior, we define the abnormal vacancy posting rate (*AbPost*) as the difference between the current posting rate and its average over the previous eight quarters (i.e., two years). We require at least four non-missing quarters to compute the abnormal vacancy posting rate. This procedure removes the time-invariant component of vacancy posting behavior. The *AbPost* variable is available for the period 2011–2017.[4]

Local Labor Market Conditions. We use three measures of labor market conditions faced by firms: relative labor market concentration (Kwan and Liu, 2018), skill requirement, and sector-level vacancy filling rate.

The relative labor market concentration of a firm is defined as the weighted share of the firm's postings relative to the top four posting firms in its local area:

$$LMS_{i,c,t} = \frac{\text{postings}_{i,c,t}/\text{postings}_{c,t}}{\text{top4}_{c,t}/\text{postings}_{c,t}} = \frac{\text{postings}_{i,c,t}}{\text{top4}_{c,t}},$$

where $\text{postings}_{i,c,t}$ is the number of postings made by firm i in county c at time t, and $\text{top4}_{c,t}$ is the total number of postings by the top four posting firms in the same county and time.

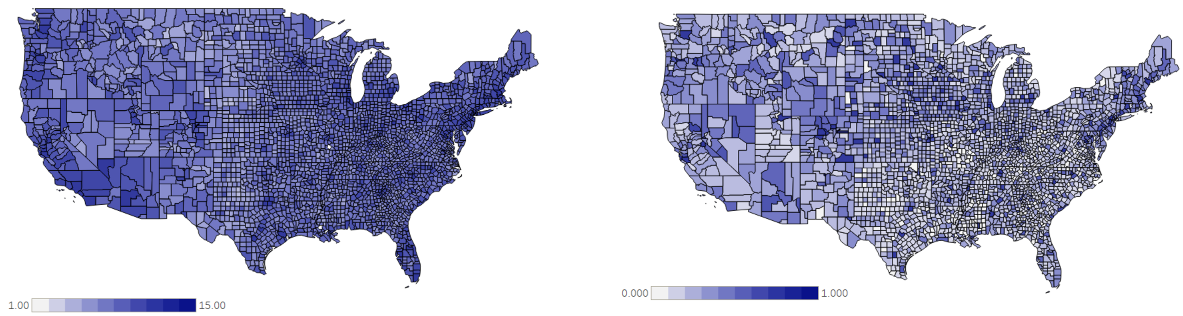
The skill requirement of a firm is defined as the share of high-skill postings in its total number of postings. A posting is classified as high-skill if it requires at least a bachelor's degree or five years of experience.

The sector-level vacancy filling rate is constructed as the ratio of sector-level hires to sector-level vacancies over the past year, using data from JOLTS.

Financial Data. In order to assess the relationship between vacancy posting rates and expected returns, we use data on stock market returns and corporate bond yields. Our stock returns sample

[4] Since the BGT database lacks data for 2008 and 2009, we use years 2007 and 2010 to construct the benchmark sample for 2011.

FIGURE 1: GEOGRAPHIC DISTRIBUTION OF VACANCY POSTINGS



(A) Log Vacancy Posting Number (B) Vacancy Posting Number per Capita

Notes: Figure 1 shows the geographic distribution of vacancy postings. Figure (A) and Figure (B) are colored based on the logarithm of the number of vacancy postings and the number of vacancy postings per capita in each county, respectively.

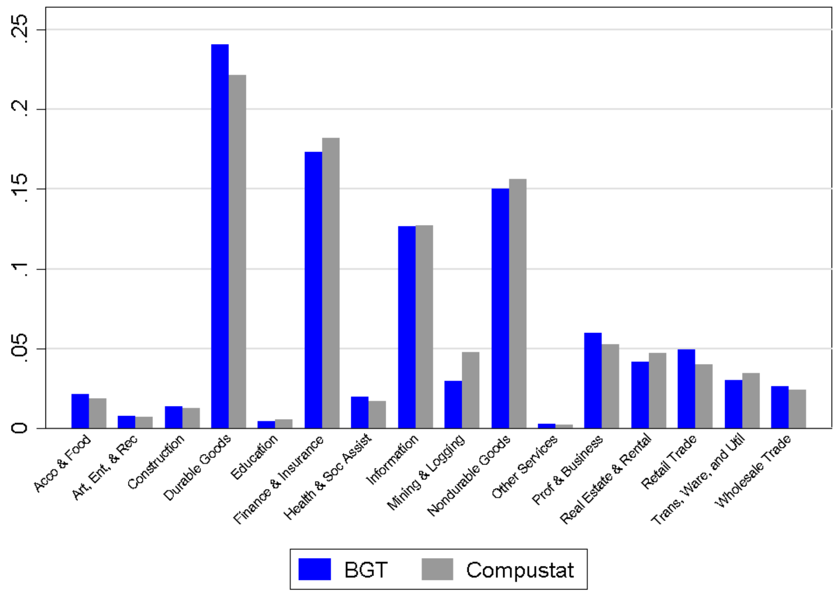
includes all primary stocks listed on the New York Stock Exchange (NYSE), the Nasdaq Stock Exchange, and the American Stock Exchange (AMEX). We exclude financial firms, utility firms, firms with less than one million dollars in total assets, and firms with fewer than fifty employees.

Monthly data on stock returns, stock prices, and shares outstanding are obtained from the CRSP database. Financial statement variables–including total assets, book equity, cash flows, debt, sales, number of employees, and capital expenditures–are sourced from the Compustat database. For cross-sectional return predictability tests, the starting date is restricted to three months after the fiscal quarter end. Data on analyst earnings forecasts are obtained from the IBES database. All variables are winsorized at the one-percent level.

Data on corporate bond yields is sourced from the TRACE database. We obtain data for the Fama-French three-factor, Carhart four-factor, and Fama-French five-factor models from Kenneth French's website.

Summary Statistics. Figure 1 plots the geographic distribution of vacancy postings in the BGT sample. Panel A displays the logarithm of the number of vacancy postings by county, which closely mirrors the population distribution across the U.S.–for instance, there is a high concentration of postings in California and along the East Coast. Panel B shows the number of postings per capita by county.

FIGURE 2: REPRESENTATIVENESS OF BURNING GLASS TECHNOLOGIES DATABASE



Notes: Figure 2 plots the distribution of firms across industries in the matched BGT sample and Compustat sample. Industries are defined at the 2-digit NAICS level.

Figure 2 compares the industry composition of publicly listed firms on major stock exchanges with that of the matched BGT sample. The figure shows that the industry composition of the matched BGT sample closely aligns with that of the broader Compustat universe.

Table 1 reports the summary statistics. Panel A compares the matched BGT sample to the full Compustat sample. The matched BGT sample covers approximately 65 percent of Compustat firms by count and 83 percent by market capitalization. The representativeness is reasonably consistent across different industries. Panel B reports firm-level summary statistics for the matched BGT sample.

3.2 Aggregate and Industry-Level Data

Aggregate data on vacancy postings is sourced from JOLTS and the Help-Wanted Index. Data on the separation rate and hiring rate are obtained from Robert Shimer's website. At the industry level, JOLTS provides data for sixteen 2-digit NAICS industries, including information on the number of vacancy postings, hires, and separations. Data on total industry employment is sourced from the Bureau of Labor Statistics.

TABLE 1: SUMMARY STATISTICS

Panel A: Summary Statistics of Vacancy Postings					
Industry	# of Postings	# of Firms		Fraction	Corr
	BGT	BGT	Comp	BGT/Comp	Ret
Mining and Logging	554,070	97	240	40.42%	0.97
Construction	246,189	45	63	71.43%	0.96
Durable Goods	4,896,820	775	1105	70.14%	0.99
Non-Durable Goods	2,884,745	485	779	62.26%	0.98
Wholesale Trade	947,234	86	121	71.07%	0.97
Retail Trade	7,897,971	159	201	79.10%	0.98
Trans, Ware, and Util	1,670,446	98	174	56.32%	0.95
Information	4,110,174	409	636	64.31%	0.99
Finance & Insurance	6,716,299	558	908	61.45%	0.98
Real Estate & Rental	1,466,703	135	237	56.96%	0.98
Prof and Business	2,636,370	193	263	73.38%	0.98
Educational Services	133,570	15	29	51.72%	0.95
Health & Social	2,617,430	65	87	74.71%	0.97
Arts, Ent, and Rec	201,781	25	36	69.44%	0.90
Acco and Food	3,727,870	69	95	72.63%	0.96
Other Services	92,124	10	13	76.92%	0.87
Total	40,799,796	3224	4987	64.65%	0.96

Panel B: Summary Statistics at Firm-Level					
	Mean	SD	10th	50th	90h
AbPost	-0.007	0.055	-0.044	-0.002	0.025
Size	7.360	1.906	4.874	7.312	9.925
BM	0.514	0.380	0.135	0.426	0.978
Prof	0.091	0.092	0.026	0.066	0.182
HN	0.046	0.166	-0.107	0.030	0.231
IK	0.011	0.012	0.002	0.008	0.025

Notes: Table 1 reports summary statistics on vacancy postings for firms listed on major stock exchanges including NYSE, Nasdaq, and AMEX between 2011 and 2017. Panel A reports the number of vacancy postings and firm count across the sixteen 2-digit NAICS industries, and the number of firms in Compustat sample. The last column of Panel A reports the time-series correlation of the value-weighted returns between the BGT matched sample and the Compustat sample. Panel B reports summary statistics for abnormal vacancy postings at the firm-level and related firm characteristics for the BGT sample.

We use returns on the value-weighted S&P 500 Composite Index as our main measure of aggregate stock market performance. In robustness tests, we also use the CRSP market index as an alternative. We denote the natural logarithm of the stock market return as r throughout our empirical analysis. We use the natural logarithm of the return on the 30-day Treasury bill as a measure of the risk-free rate, denoted by r^f. The log excess stock return is therefore defined as $r - r^f$. Returns on U.S. corporate bonds are denoted by r^b, and the log excess bond return is $r^b - r^f$.

We control for standard equity return predictors established in the literature. Specifically, we include the following variables. The aggregate capital investment rate, *ik*, is defined as private non-residential fixed investment over the corresponding capital stock, sourced from the Bureau of Economic Analysis (Cochrane, 1991; Philippon, 2009). The log dividend-price ratio, *dp*, is measured as the natural logarithm of dividends paid on the S&P 500 index divided by the price of the S&P 500 index (Campbell and Shiller, 1988; Fama and French, 1988). The log earnings-price ratio, *ep*, is measured as the natural logarithm of earnings on S&P 500 companies divided by the price of the S&P 500 index (Campbell and Shiller, 1988). The consumption-wealth ratio, *cay*, is constructed as in Lettau and Ludvigson (2001).[5] The relative bill rate, *tbill*, is calculated as the three-month Treasury bill rate minus its four-quarter backward moving average (Hodrick, 1992).

4 Empirical Results

This section reports our main empirical results. First, in Sections 4.1 and 4.2, we document two robust empirical findings that are consistent with predictions of a simple model: a negative expected return–vacancy relationship and a positive expected cash flow–vacancy relationship. Next, in Section 4.3, we show that both the negative expected return–vacancy relationship and the positive expected cash flow–vacancy relationship are attenuated when firms operate under more favorable labor market conditions.

4.1 Expected Return-Vacancy Relationship

In this section, we document a strong negative unconditional relationship between expected returns and vacancy posting rates. We begin by presenting evidence on the negative expected return–vacancy relationship using realized stock returns. We then confirm this result using implied cost of capital as an alternative proxy for expected equity returns. Finally, we demonstrate that the negative expected return–vacancy relationship also holds in the corporate bond market.

[5] Data on the consumption-wealth ratio are from Sydney Ludvigson's website.

TABLE 2: FUTURE RETURN AND VACANCY POSTING RATE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Future Return				
AbPost	-2.472***	-2.480***	-2.425***	-2.232***	-2.334***	-2.411***	-2.518***	-2.047**
	(-2.697)	(-2.752)	(-2.664)	(-2.752)	(-2.665)	(-2.658)	(-2.776)	(-2.560)
HN		-0.264						0.021
		(-0.578)						(0.053)
IK			-22.366***					-19.731***
			(-3.874)					(-3.697)
R&D				4.636				6.049
				(1.023)				(1.393)
Size					-0.080			-0.008
					(-1.497)			(-0.164)
BM						0.040		-0.177
						(0.299)		(-1.421)
Prof							5.293***	6.225***
							(4.652)	(5.948)
Obs.	137,679	137,679	137,679	137,679	137,679	137,679	137,679	137,679
R^2	0.003	0.005	0.005	0.012	0.009	0.010	0.010	0.037

Notes: Table 2 reports the regression results from the cross-sectional stock return predictability regressions. The Fama and MacBeth (1973) cross-sectional regressions are used. Data frequency is monthly. t-statistics are reported in parentheses. *Obs*. denotes the number of observations. Returns are expressed in percentages. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

4.1.1 Stock Market

We exploit cross-sectional variation in stock returns and *AbPost*, controlling for other firm characteristics. Specifically, we estimate Fama-MacBeth regressions of monthly firm-level returns on lagged *AbPost*, controlling for standard cross-sectional return predictors.

Table 2 reports monthly panel regression results, with Fama–MacBeth t-statistics reported in parentheses. The coefficient on *AbPost* is significantly negative across all model specifications, indicating that higher posting rates predict lower subsequent stock returns. In the univariate regression, the coefficient on *AbPost* is -2.47, implying that a one-standard-deviation increase in *AbPost* is associated with a decrease in monthly stock returns of 0.14 percent, or 1.68 percent per annum.

Columns (2)–(7) report regression results controlling for known cross-sectional return predictors: employment growth rate (HN), capital investment rate (IK), R&D investment rate (R&D),

size, book-to-market ratio, and profitability. The coefficient on *AbPost* remains stable, around -2.50, indicating robustness to the inclusion of these controls. In the final column, we jointly include *AbPost* and all other explanatory variables. The coefficient on *AbPost* remains negative and statistically significant; the point estimate suggests that a one-standard-deviation increase in *AbPost* is associated with a 0.11 percent decline in monthly stock returns.

Table A.1 in the Appendix reports average monthly returns and model-adjusted alphas for *AbPost*-sorted portfolios and the corresponding long-short strategy. Column (1) shows that sorting firms into quintiles by *AbPost* generates a spread in excess returns of 0.37 percent per month, or 4.45 percent annually, between the lowest and highest quintile portfolios. This spread is statistically significant at the 5 percent level, with a t-statistic of 2.41. The alphas remain large and statistically significant after adjusting for the CAPM, Fama–French three-factor, Carhart four-factor, and Fama–French five-factor models. In untabulated results, we further sort firms into portfolios within their Fama-French 30 industry groups to isolate the within-industry effect. Our results suggest that approximately 25 percent of the cross-sectional return predictability of vacancy posting rates is attributable to the industry classification.

One concern with the baseline results is the relatively short sample period, which may limit the reliability of the estimated long-short strategy returns.[6] In order to alleviate this concern, we redo the baseline analysis at the industry level. JOLTS provides vacancy posting data starting from 2001 for sixteen 2-digit NAICS industries; this allows us to construct the *AbPost* variable at the industry level. We sort industries each quarter into three portfolios based on their *AbPost* values. Industry returns are value-weighted based on the underlying firms; portfolio returns are equal-weighted based on the underlying industries.

Table A.2 in the Appendix reports the subsequent three months' excess returns of these three portfolios. The average unadjusted long-short strategy excess return is 0.62 percent per month or 7.44 percent per year, confirming the negative expected return-vacancy relationship documented at the firm-level. The CAPM, Fama–French three-factor, Carhart four-factor, and Fama–French five-factor adjusted alphas are 0.58, 0.61, 0.68, and 0.61 percent per month, respectively. All excess

[6] Due to data availability, many studies using online data rely on relatively short sample periods. For example, Antweiler and Frank (2004) use Yahoo! message board data from 2000; Da, Engelberg and Gao (2011) use Google Trends data from 2004 to 2008 to measure investor attention; and Sheng (2025) uses Glassdoor data from 2012 to 2016 to study employee expectations and their effects on stock returns.

returns and adjusted alphas are statistically significant at the 5 percent level.

Moreover, we find a negative and significant relationship between vacancy posting rates and future aggregate equity returns in a much longer time series. Table A.3 in the Appendix reports the return predictability results for aggregate vacancy posting rates over the past 70 years. The adjusted R^2 values are 2 percent for both one-quarter and two-quarter ahead returns.

Aggregate Time-Series Results. In the Online Appendix C.1, we introduce a new measure—the employee valuation ratio—and study its properties. This ratio is motivated by the search-and-matching literature and incorporates information on both the aggregate vacancy posting rate and labor market conditions. The employee valuation ratio emerges as a strong predictor of aggregate stock and corporate bond market returns, and it subsumes the predictive power of just the aggregate vacancy posting rate. These results suggest that the combination of aggregate vacancy posting rates and labor market conditions captures meaningful variation in aggregate risk premia.

4.1.2 Implied Cost of Capital

Next, we use measures of implied cost of capital (ICC) as alternative proxies for expected returns. A key advantage of ICC measures over realized returns is that they are less sensitive to the noise and quality of stock return data. We employ three ICC measures: the GLS measure from Gebhardt, Lee and Swaminathan (2001), the HVDZ measure from Hou, Van Dijk and Zhang (2012), and the TWZ measure from Tang, Wu and Zhang (2013). The GLS measure is based on analyst earnings forecasts, while the HVDZ and TWZ measures use regression-based approaches to forecast the level of earnings (HVDZ) and the return on equity (TWZ), respectively.

The results are summarized in Table 3. For each set of results, we report both the univariate specification and the specification controlling for size, book-to-market, profitability, and investment rate. The coefficient estimates on *AbPost* are negative and statistically significant across all specifications, indicating a negative relationship between ICC and the vacancy posting rate. The economic magnitudes are generally smaller than those based on average realized future returns. For example, using the HVDZ measure, a one-standard-deviation increase in *AbPost* is associated with a decrease in ICC of approximately 0.1 percent per month, or 1.20 percent annually. Overall, consistent with the results based on realized returns, we find a negative relationship between the

TABLE 3: IMPLIED COST OF CAPITAL AND VACANCY POSTING RATE

(Percentage)	GLS		HVDZ		TWZ	
	(1)	(2)	(3)	(4)	(5)	(6)
AbPost	-0.820***	-0.598**	-1.791***	-1.041***	-1.143***	-0.541***
	(-2.779)	(-2.200)	(-7.125)	(-4.913)	(-6.844)	(-5.805)
Size		-0.260***		-0.294***		-0.260***
		(-80.014)		(-48.948)		(-72.054)
BM		0.386***		0.085***		0.194***
		(23.012)		(2.796)		(20.489)
Prof		2.548***		1.442***		1.741***
		(15.379)		(4.517)		(17.587)
IK		8.084***		3.796***		2.310***
		(9.867)		(2.856)		(5.204)
Obs.	24,653	24,653	26,592	26,592	33,987	33,987
Adj. R^2	0.002	0.238	0.005	0.164	0.005	0.334

Notes: Table 3 reports coefficients from regressing the implied cost of capital on vacancy posting rate. *GLS* is the cost of capital measure in Gebhardt, Lee and Swaminathan (2001). *HVDZ* is the cost of capital measure in Hou, Van Dijk and Zhang (2012). *TWZ* is the cost of capital measure in Tang, Wu and Zhang (2013). Data has quarterly frequency. Standard errors are double clustered by time and firm. Time fixed effects are included in all regressions. *t*-statistics are reported in parentheses. *Obs*. denotes the number of observations. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

implied cost of capital and the vacancy posting rate.

4.1.3 Corporate Bond Yield

We examine the relationship between vacancy posting rates and expected returns using corporate bond yields. Specifically, we run Fama-MacBeth regressions of quarterly corporate bond yields at the firm level on lagged *AbPost*, controlling for other cross-sectional firm characteristics. Similar to ICCs, an advantage of using corporate bond yields as a measure of expected returns–compared to realized returns–is that bond yields are less sensitive to the quality of stock return data.

Table 4 reports the results. In the univariate regression, the point estimate on *AbPost* is -6.99, indicating that a one-standard-deviation increase in *AbPost* is associated with a decrease in the corporate bond yield by 15 percent of the sample average. The coefficient estimates on *AbPost* remain statistically significant at the 1 percent level across all bivariate regressions that control for

TABLE 4: CORPORATE BOND YIELD AND VACANCY POSTING RATE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Corporate Bond Yield							
AbPost	-6.988***	-6.176***	-6.968***	-5.657***	-5.042***	-6.725***	-6.775***	-3.276**
	(-4.412)	(-3.994)	(-4.440)	(-3.661)	(-3.425)	(-4.272)	(-4.184)	(-2.340)
HN		1.696***						1.100*
		(3.129)						(2.013)
IK			-6.616*					9.993**
			(-1.863)					(2.555)
R&D				55.981***				55.364***
				(11.754)				(9.346)
Size					-0.876***			-0.726***
					(-31.486)			(-22.391)
BM						0.269***		0.449***
						(2.808)		(5.303)
Prof							7.617***	6.276***
							(10.125)	(8.622)
Obs.	17,977	17,977	17,977	17,977	17,977	17,977	17,977	17,977
R^2	0.002	0.002	0.002	0.014	0.034	0.003	0.010	0.051

Notes: Table 4 reports coefficients from regressing corporate bond yield on *AbPost*. The Fama and MacBeth (1973) cross-sectional regressions are used. Data has quarterly frequency. t-statistics are reported in parentheses. *Obs.* denotes the number of observations. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

individual firm characteristics. Column (8) reports the results from the full specification including all controls. In this case, the magnitude of the coefficient on *AbPost* declines to -3.28 but remains statistically significant at the 5 percent level. In sum, we find a negative relationship between vacancy posting rates and expected corporate bond returns.

4.2 Expected Cash Flow-Vacancy Relationship

In this section, we study the relationship between expected cash flows and vacancy posting rates, controlling for known cash flow predictors. We measure a firm's expected cash flow using either the average realized future earnings or analyst earnings forecasts. We use a version of the cross-sectional profitability model from Fama and French (2000, 2006) and Hou, Van Dijk and Zhang

TABLE 5: EXPECTED CASH FLOW AND VACANCY POSTING RATE

Dep. Variable*100	(1)	(2)	(3)	(4)	(5)	(6)
		Future ROA			Forecasted ROA	
AbPost	8.271***	2.357***	2.218***	13.063***	3.673***	3.646***
	(6.880)	(4.528)	(4.247)	(6.802)	(3.059)	(3.153)
ROA		0.685***	0.644***		0.969***	1.039***
		(34.863)	(26.348)		(15.650)	(14.234)
Div			-477.911***			-2,162.557**
			(-3.280)			(-2.408)
DDiv			0.030			0.779**
			(0.207)			(2.484)
NegE			-0.622***			0.973***
			(-5.576)			(3.656)
AC			-3.180**			-12.578***
			(-2.519)			(-7.542)
R^2	38,140	38,140	38,140	37,362	37,362	37,362
Obs.	0.018	0.478	0.481	0.011	0.423	0.433

Notes: Table 5 reports estimation results for a number of cross-sectional cash flow predictability regressions. The regression specification is

$$Y_{i,t} = \alpha + \beta_1 AbPost_{i,t-1} + \beta_2 ROA_{i,t-1} + \beta_3 Div_{i,t-1} + \beta_4 DDiv_{i,t-1} + \beta_5 NegE_{i,t-1} + \beta_6 AC_{i,t-1} + \varepsilon_{i,t}.$$

$Y_{i,t}$ is either realized future earnings or analyst forecasted earnings scaled by total assets. This table reports results based on panel regressions at the quarterly frequency with time fixed effects. Standard errors are clustered at the firm-level. *ROA* is constructed as earnings over total assets. Controls include *NegE*, *Div*, *DDiv*, and *AC*. t-statistics are reported in parentheses. *Obs*. denotes the number of observations. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

(2012), specified as follows:

$$Y_{i,t} = \alpha + \beta_1 \text{AbPost}_{i,t-1} + \beta_2 \text{ROA}_{i,t-1} + \beta_3 \text{Div}_{i,t-1} + \beta_4 \text{DDiv}_{i,t-1} + \beta_5 \text{NegE}_{i,t-1} + \beta_6 \text{AC}_{i,t-1} + \varepsilon_{i,t}, \tag{2}$$

where i indexes firms and t indexes time. $Y_{i,t}$ is either the realized return on assets in the next period or the analyst forecast of next-period earnings. *ROA* denotes the return on assets, and *AbPost* is the vacancy posting rate. *Div* is dividends scaled by total assets, *DDiv* is an indicator variable for dividend payers, *NegE* is an indicator for firms with negative earnings, and *AC* represents absolute accruals as in Sloan (1996).

The coefficient of interest is β_1. Based on Prediction 2 of the simple model, we expect a positive relationship between expected cash flows and vacancy rates, or a positive β_1. Table 5 reports the cross-sectional results using the Fama-MacBeth regression method. In Column (1), *AbPost* is the only explanatory variable, and the coefficient estimate is positive and highly statistically significant. Columns (2) and (3) include controls for past firm's *ROA* and other firm characteristics. While the point estimate on *AbPost* decreases slightly, it remains positive and statistically significant at the 1 percent level. Overall, the results support the model's prediction of a positive relationship between expected cash flows and vacancy rates.

Columns (4)–(6) of Table 5 use analyst earnings forecasts as the dependent variable. The coefficient estimates on *AbPost* are again positive and significant at the 1 percent level.

The asset pricing literature documents a positive relationship between expected returns and firm profitability. Since vacancy posting rates negatively predict future returns but positively predict future cash flows, a large spread should emerge when stocks are sorted into portfolios based on both profitability and vacancy rates. In untabulated results, we confirm this prediction: both the profitability and *AbPost* strategies become stronger when stocks are double-sorted by profitability and vacancy posting rates.

4.3 Role of Labor-Market Conditions

According to Predictions 3a and 3b from Section 2, the relationship between expected returns and vacancy rates, as well as between expected cash flows and vacancy rates, should be weaker for firms operating under more favorable labor market conditions. When vacancies are relatively difficult to fill, or when labor market conditions are unfavorable, variations in vacancy posting rates become more informative about firms' underlying expectations of returns and cash flows.

We use three measures of firm-specific labor market conditions: (1) relative labor market concentration (Kwan and Liu, 2018); (2) skill requirements; and (3) sector-level vacancy filling rate from JOLTS. Since labor market conditions tend to be more favorable for firms with relatively high labor market concentration and low skill requirements, we expect the predictive power of vacancy postings to be weaker for such firms. The sector-level vacancy filling rate is a direct measure of labor market tightness; however, it is only available for a subset of sectors in JOLTS.

We construct binary indicators for every measure of labor market conditions that we consider;

Table 6: Labor-Market Conditions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
			Future Return						Future ROA			
AbPost	-3.999***	-3.922***	-4.742***	-3.748**	-3.763***	-3.925***	11.415***	9.748***	9.323***	3.569***	2.231*	2.924***
	(-2.716)	(-3.156)	(-3.123)	(-2.555)	(-3.200)	(-2.828)	(7.876)	(5.780)	(8.729)	(3.752)	(1.967)	(4.558)
AbPost$\times\mathbf{1}_{\text{Power>Median}}$	2.360*			2.295*			-9.854***			-3.798***		
	(1.779)			(1.732)			(-6.206)			(-3.730)		
$\mathbf{1}_{\text{Power>Median}}$	0.045			0.207***			1.292***			0.355***		
	(0.421)			(3.081)			(17.115)			(8.973)		
AbPost$\times\mathbf{1}_{\text{Skill<Median}}$		2.438**			2.416**			-6.588***			-1.833	
		(2.262)			(2.279)			(-3.496)			(-1.498)	
$\mathbf{1}_{\text{Skill<Median}}$		0.038			-0.053			0.816***			0.254***	
		(0.286)			(-0.484)			(10.428)			(4.937)	
AbPost$\times\mathbf{1}_{\text{Yield>Median}}$			3.119*			2.543			-6.776***			-3.571***
			(1.832)			(1.549)			(-4.246)			(-3.093)
$\mathbf{1}_{\text{Yield>Median}}$			-0.329**			-0.160			0.337***			0.022
			(-2.046)			(-1.196)			(2.897)			(0.232)
Controls	N	N	N	Y	Y	Y	N	N	N	Y	Y	Y
R^2	0.006	0.005	0.002	0.030	0.029	0.037	0.046	0.021	0.022	0.483	0.481	0.480
Obs.	116,831	137,943	123,160	116,831	137,943	123,160	38,130	38,130	38,130	38,210	38,130	38,130

Notes: Table 6 reports estimation results for a number of cross-sectional tests. The tests are based on the Fama–MacBeth regression method, where the dependent variable is either the monthly firm stock return or *ROA*. The set of explanatory variables includes lagged *AbPost* and interaction terms. Interaction terms are constructed using indicator variables described in the text. Controls include employment growth, investment rate, size, book-to-market, momentum, and profitability. t-statistics are reported in parentheses. Returns are expressed in percentages, and future *ROAs* are multiplied by 100. *Obs*. denotes the number of observations. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

each indicator variable equals one if the firm is above the sample median with respect to that measure in a given time period, and zero otherwise.

Expected Returns. We first test Prediction 3a by studying how the expected return–vacancy relationship varies with firms' labor market conditions. Columns (1), (2), and (3) of Table 6 report results based on relative labor market concentration, the skill requirement rate, and the sector-level vacancy filling rate, respectively. The point estimates on *AbPost* are -4.00, -3.92, and -4.74 in Columns (1), (2), and (3), respectively, and are highly statistically significant. The interaction terms are also statistically significant, with coefficients of 2.36, 2.44, and 3.12, indicating that the slope of the relationship between expected returns and vacancy rates decreases by more than fifty percent for firms operating under more favorable labor market conditions, as measured by the three respective proxies.

Columns (4), (5), and (6) include additional controls for standard cross-sectional stock return predictors, and the results remain qualitatively similar. The coefficient estimate for the interaction term based on the sector-level vacancy filling rate is no longer statistically significant, but it remains positive and economically sizable.

In sum, our findings support Prediction 3a: the negative relationship between expected returns and vacancy rates is attenuated for firms facing more favorable labor market conditions.

Expected Cash Flow. Next, we test Prediction 3b by studying how the expected cash flow–vacancy relationship varies with firms' labor market conditions. Prediction 3b states that the positive relationship between expected cash flows and vacancy rates should be weaker for firms operating in more favorable labor market environments.

Columns (7)–(9) of Table 6 report our results. The point estimates on *AbPost* are 11.42, 9.75, and 9.32 in Columns (7), (8), and (9), respectively, and are all statistically significant. The interaction terms are negative and statistically significant, with coefficients of -9.85, -6.59, and -6.78, suggesting that the strength of the positive cash flow–vacancy relationship declines to roughly twenty percent of its original magnitude for firms in more favorable labor market conditions.

Columns (10)–(12) additionally include current *ROA* and controls. In these specifications, the point estimates on *AbPost* decline to about one-third of their original values but remain statistically significant. The interaction terms remain negative and significant when using relative labor market concentration and the sector-level vacancy filling rate. While the interaction term based on the skill requirement rate is no longer statistically significant, its magnitude remains large and its sign negative.

Overall, the results support Prediction 3b: the positive relationship between expected cash flows and vacancy rates is attenuated for firms operating in more favorable labor market conditions.

5 Quantitative Model

In this section, we develop a general equilibrium model of firm dynamics to jointly study labor market frictions and the cross-section of stock returns. Time in the model is discrete and the horizon is infinite. The economy is populated by heterogeneous firms and a household. The household is comprised of a unit mass of members, each of them being either employed or unemployed at any point of time. The household owns all firms.

5.1 Environment

Every firm i has access to a production technology with decreasing returns to scale:

$$y(Z,z,n) = e^{Z} e^{z} n^{\nu}$$

with $\nu \in (0,1)$. Labor n is the only factor of production. The production function is scaled by an aggregate component Z and idiosyncratic component z. Aggregate productivity component Z affects all firms simultaneously; it follows an AR(1) process:

$$Z = \rho_Z Z_{-1} + \varepsilon^Z, \qquad \varepsilon^Z \sim \mathcal{N}(0, \sigma_Z), \tag{3}$$

where $\rho_Z \in (0,1)$. Idiosyncratic component z follows an AR(1) process with the persistence parameter $\rho_z \in (0,1)$:

$$z = \rho_z z_{-1} + \varepsilon^z, \tag{4}$$

Idiosyncratic productivity shock ε^z is drawn from the normal distribution with mean 0 and variance

σ_z^2; we assume that idiosyncratic shocks are independent across firms and over time.

Firms post a number of job vacancies vc_{it} to attract unemployed workers. Vacancies are filled via a constant returns to scale matching function:

$$G(U_t, V_t) = \frac{U_t V_t}{(U_t^{\iota} + V_t^{\iota})^{\frac{1}{\iota}}}, \tag{5}$$

whereby $V_t = \int vc_{it} \mathrm{d}\mu$ is the aggregate number of posted vacancies, U_t denotes the aggregate mass of unemployed workers, and parameter $\iota > 0$ governs the curvature of the matching function. Distribution of firms over idiosyncratic states μ will be described below.

It is convenient to define the vacancy-unemployment ratio $\theta_t \equiv \frac{V_t}{U_t}$. It follows that the job finding rate is $f(\theta_t) \equiv \frac{G(U_t,V_t)}{U_t} = \left(1+\theta_t^{-\iota}\right)^{-\frac{1}{\iota}}$ and the vacancy filling rate is $q(\theta_t) \equiv \frac{G(U_t,V_t)}{V_t} = (1+\theta_t^{\iota})^{-\frac{1}{\iota}}$. The vacancy-unemployment ratio θ_t measures the market tightness from the firm's perspective since the vacancy filling rate is decreasing in θ_t, $q'(\theta_t) < 0$.

Firms enter period t with a predetermined idiosyncratic level of labor, n. We assume that jobs are destroyed at a constant rate s per period.[7] Employment at the firm level evolves according to the following law of motion:

$$n_{it+1} = (1-s)n_{it} + q_i(\theta_t)vc_{it}, \tag{6}$$

where $q_i(\theta_t)vc_{i,t}$ represents the mass of new hires.

The amount of labor in period $t+1$ is determined by market tightness and the number of vacancies posted in period t, vc_{it}. We assume that vacancy posting is costly, and firms have to pay κ units of output per posted vacancy. Besides, firms pay quadratic adjustment costs:

$$AC(n, vc) = \frac{\varphi}{2}\left(\frac{vc}{n}\right)^2 n,$$

where parameter φ captures the extent of convex adjustment costs in the model. The convex cost component reflects the fact that higher costs are incurred for more rapid changes.

Firms may operate under either favorable or unfavorable firm-specific labor market conditions. Specifically, in each period, a firm faces a favorable labor market with probability p^F; in this case,

[7] A constant separation rate is routinely assumed in asset pricing literature for tractability (e.g., Belo, Lin and Bazdresch, 2014; Kuehn, Simutin and Wang, 2017). In the data, the flow rate from employment to unemployment is strongly countercyclical (Baydur and Mukoyama, 2020).

the vacancy filling rate is given by $q_i(\theta_t) = (1+\Delta)q(\theta_t)$. With the complementary probability $1-p^F$, the firm faces an unfavorable labor market, whereby the vacancy filling rate is $q_i(\theta_t) = (1-\Delta)q(\theta_t)$. Parameter Δ captures the percentage deviation of the favorable and unfavorable vacancy filling rates from the prevailing aggregate rate $q(\theta_t)$. We assume that the realization of labor market conditions each firm faces is independent across firms and over time.

Firms' revenues, net of vacancy posting costs, adjustment costs and payments to labor, are distributed to the representative household as dividends. We assume there are no financial frictions, and thus do not impose restrictions on firms' dividend payments.

The economy is populated by a household comprised of a unit mass of identical members, with N_t employed and $U_t = 1-N_t$ unemployed. Thus, N_t and U_t represent the employment and unemployment rate, respectively. The household pools the income of all its members before consumption takes place.

Discussion of Assumptions. One can interpret the deviation of a firm's vacancy-filling rate from the aggregate equilibrium rate $q(\theta_t)$ as capturing, among other factors, the vacancy posting behavior of local firms or firm-specific shifts in skill requirements. We explicitly use these proxies for firm-specific labor market conditions in our empirical analysis.

In the model, we remain agnostic about the exact source of firm-specific labor market conditions and, therefore, do not endogenize the firm-specific vacancy-filling rate. The objective of the quantitative model is to study the implications of labor market conditions for the predictive power of vacancy rates. Accordingly, we treat these conditions as given and do not model their origin.[8]

5.2 Firm Optimization

Let $\mathbf{S}$ denote the aggregate state that consists of the distribution of firms over the idiosyncratic states $\mu = \mu(n,z)$, as well as the value of an aggregate shock Z. The firm enters the period with some pre-determined level of labor n. Idiosyncratic productivity z is realized at the beginning of the period. Let $v(n,z;\mathbf{S})$ denote the value of the firm at the start of the period given the idiosyncratic state (n,z) and the aggregate state $\mathbf{S}$.

[8]One way to endogenize the effective firm-level vacancy-filling rate is by allowing firms to choose their recruiting intensity. Recruiting intensity has been shown to account for variation in hires (e.g., Davis, Faberman and Haltiwanger, 2013). In the model, firm-specific recruiting intensity can decline, for instance, when potential hires have low returns.

After the production stage takes place, firms learn the idiosyncratic condition of the labor market. Thus, the value of the firm at the start of the period can be written as:

$$v(n,z;\mathbf{S}) = \pi(n,z;\mathbf{S}) + p^F v^F(n,z;\mathbf{S}) + (1-p^F)v^U(n,z;\mathbf{S}), \tag{7}$$

where firm's flow profits π are defined as:

$$\pi(n,z;\mathbf{S}) = e^Z e^z n^\nu - W(n,z;\mathbf{S})n. \tag{8}$$

Objects v^F and v^U in (7) are values the firm attains in case of favorable and unfavorable labor market conditions, respectively.

Favorable Labor Markets. If the firm operates under favorable labor market conditions, then it solves the following programming problem

$$v^F(n,z;\mathbf{S}) = \max_{n' \geq 0} -\kappa vc - AC(n,vc) + \mathbb{E}[M(\mathbf{S},\mathbf{S}')v(n',z';\mathbf{S}')], \tag{9}$$

$$n' = (1-s)n + (1+\Delta)q(\theta(\mathbf{S}))vc, \tag{10}$$

$$AC(n,vc) = \frac{\varphi}{2}\left(\frac{vc}{n}\right)^2 n, \tag{11}$$

where $M(\mathbf{S},\mathbf{S}')$ is a stochastic discount factor.[9]

Unfavorable Labor Markets. The value of a firm operating under unfavorable labor market conditions v^U solves a similar to (9)-(11) programming problem with the only difference that the law of motion for employment is

$$n' = (1-s)n + (1-\Delta)q(\theta(\mathbf{S}))vc.$$

Wages. Provided that there are frictions in the matching process between unemployed workers and firms, unemployment and rents emerge in equilibrium. These rents are shared between firms

[9]It is common in the literature not to explicitly impose a non-negativity constraint on vacancy positing; in our model vacancy posting is negative in only about 2 percent of cases. Petrosky-Nadeau, Zhang and Kuehn (2018) is one exception where the non-negativity constraint is explicitly imposed in the solution algorithm.

and employees. We follow Stole and Zwiebel (1996) and Kuehn, Simutin and Wang (2017) and assume Nash bargaining wages in multi-worker firms with decreasing returns to scale technology. Specifically, firms renegotiate wages every period with their workforce based on individual Nash bargaining.

We assume that workers' bargaining weight is governed by a parameter $\eta \in (0,1)$. If workers choose not to work, they receive an unemployment benefit of $b > 0$. If they choose to work, they receive compensation for the increase in the firm's output (i.e., the marginal product of labor) as well as for the savings in hiring costs that the firm would have otherwise incurred by posting a new vacancy. As a result, the equilibrium wage for a firm indexed by idiosyncratic and aggregate state $(n, z; \mathbf{S})$ is given by:

$$W(n,z;\mathbf{S}) = \eta \left[\frac{\nu}{1-\eta(1-\nu)} \frac{y(n,z;\mathbf{S})}{n} + \kappa\theta(\mathbf{S}) \right] + (1-\eta)b, \tag{12}$$

where the constant premultiplying the marginal product of labor captures the reduction in wages due to the decreasing returns to scale assumption, and the second term inside the brackets reflects the fact that workers can extract higher wages when labor markets are tight.

5.3 Household

The household is comprised of employed and unemployed members; their incomes are pooled before consumption is chosen. We consider preferences with external habit formation of the following form:

$$U = \frac{(C_t - H_t)^{1-\sigma}}{1-\sigma}, \tag{13}$$

where H_t is a habit stock (Campbell and Cochrane, 1999; Jermann, 1998). We define the habit stock H_t to capture the idea that utility over current consumption is evaluated relative to the past consumption. Specifically, we first define the surplus consumption ratio as

$$S_t := \frac{C_t - H_t}{C_t}, \tag{14}$$

and then define the law of motion for S_t:

$$S_{t+1} = \bar{S}^{1-\rho_H} S_t^{\rho_H} \left(\frac{C_{t+1}}{C_t} \right)^{\lambda_H}, \tag{15}$$

where parameter ρ_H governs habit persistence, and λ_H is sensitivity of habit to consumption growth.

The household owns firms.[10] Thus, the stochastic discount factor used by firms is equal to the household's intertemporal marginal rate of substitution:

$$M(\mathbf{S}, \mathbf{S}') = \beta \frac{U_C'(C(\mathbf{S}')S')}{U_C'(C(\mathbf{S})S)}. \tag{16}$$

The definition of equilibrium is relegated to Online Appendix D.1.

5.4 Parameterization and Model Fit

Fixed Parameters. We set the model period to one quarter. The labor share is set to $\nu = 0.67$. The curvature of the utility function is set to $\sigma = 2$ following Campbell and Cochrane (1999). The separation rate is set to 12 percent, consistent with the commonly used monthly separation rate of 3 percent in the literature (Davis, Faberman and Haltiwanger, 2013; Petrosky-Nadeau, Zhang and Kuehn, 2018). The persistence of the idiosyncratic productivity process ρ_z is fixed at 0.90, and the standard deviation of productivity shocks σ_z is set to 0.05. These values are in the ballpark of those commonly used in the firm dynamics literature. The curvature of the matching function ι is set to 1.25 (Petrosky-Nadeau, Zhang and Kuehn, 2018). The sensitivity of external habit with respect to the consumption bundle λ_H is set equal to $\frac{1}{\bar{S}} - 1$ (Chen, 2017), where $\bar{S}$ denotes the steady-state value of surplus consumption. The bargaining power of workers η is set to 0.04 (Petrosky-Nadeau, Zhang and Kuehn, 2018) and the unemployment benefit b is set to 0.85 (Rudanko, 2011).

Fitted Parameters. The time preference parameter β is chosen to match the average return on 90-day Treasury bills. The quadratic adjustment cost parameter φ governs the cross-sectional dis-

[10] Provided that our focus is on the cross-section of stock returns, we do not model heterogeneity in stock market participation across agents. This margin has been shown to play an important role in some contexts, such as the transmission of monetary policy (Melcangi and Sterk, 2024).

TABLE 7: AGGREGATE ASSET PRICING AND BUSINESS CYCLE MOMENTS

Business Cycle Statistics			*Asset Pricing Moments*		
Moment	Data	Model	*Moment*	Data	Model
$\sigma(Y)$	1.80	1.98	$\mathbb{E}[r^f]$	0.89	0.78
$\rho(C,Y)$	0.91	0.99	$\mathbb{E}[r^e - r^f]$	6.36	6.90
$\rho(N,Y)$	0.90	0.62	$\sigma[r^f]$	1.82	7.90
$\sigma(C)/\sigma(Y)$	0.82	0.99	$\sigma[r^e - r^f]$	16.52	22.70
$\sigma(N)/\sigma(Y)$	0.67	0.90	$AC_1(r^f)$	0.84	0.95
			$AC_1(r^e - r^f)$	0.08	0.09

Notes: Table 7 reports asset pricing and business cycle statistics in the data and model. The symbols have the following meaning: r^f, risk-free rate, r^e, return to equity, Y, output, C, consumption, N, employment, $\sigma(\cdot)$, standard deviation, $\rho(\cdot)$, correlation, AC_1, first-order autocorrelation. Only levels of macro aggregates (C,N and Y) were log-differenced and HP-filtered with the smoothing parameter of 1600. Business cycle statistics are quarterly and asset return moments are annualized and reported in percentage terms. We simulate the economy for 500 quarters; the first 200 periods are discarded to reduce the impact of initial conditions.

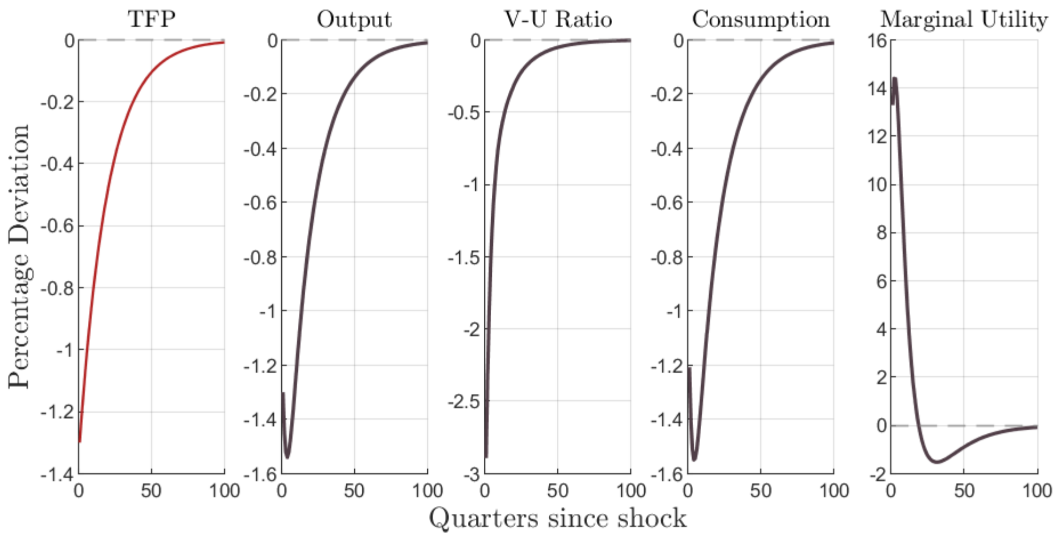
persion in vacancy posting rates. The vacancy posting cost κ is chosen to match unemployment volatility. The probability of favorable labor market conditions p^F and the gap between favorable and unfavorable vacancy-filling rates Δ are chosen to fit the 10th and 90th percentiles of the vacancy rate distribution. The persistence of aggregate TFP ρ_Z and the standard deviation of TFP innovations σ_Z are informed by the persistence of aggregate output and its volatility. The steady-state surplus consumption $\bar{S}$ is chosen to match the mean Sharpe ratio of 0.4. The habit persistence parameter ρ_H is informative about the persistence of the price-dividend ratio. Table A.4 in the Appendix summarizes the model's parameterization.

Business Cycle and Aggregate Asset Pricing Moments. The model matches standard business cycle statistics (left panel of Table 7). The volatility of aggregate output is targeted; aggregate employment and consumption are less volatile than output in both the model and the data. All macroeconomic aggregates are highly correlated with each other since there is a single aggregate shock.

The model also matches important asset pricing moments. Specifically, the risk-free rate is small and relatively stable, and the equity premium is large and volatile.[11] While the latter effect typically arises in habit formation models (e.g., Jermann, 1998; Campbell and Cochrane, 1999),

[11] We compute the (gross) risk-free rate as $R_t^f = \frac{1}{\mathbb{E}_t M(\mathbf{S},\mathbf{S}')}$, and the expected stock return for a firm with state (n,z) at time t is defined as $\mathbb{E}_t\left[\frac{v_{t+1}(n',z')}{v_t(n,z)-d_t(n,z)}\right]$, where $d_t(n,z) = y_t(n,z) - W_t n - AC(n,vc) - \kappa \times vc$.

FIGURE 3: IMPULSE-RESPONSE FUNCTIONS



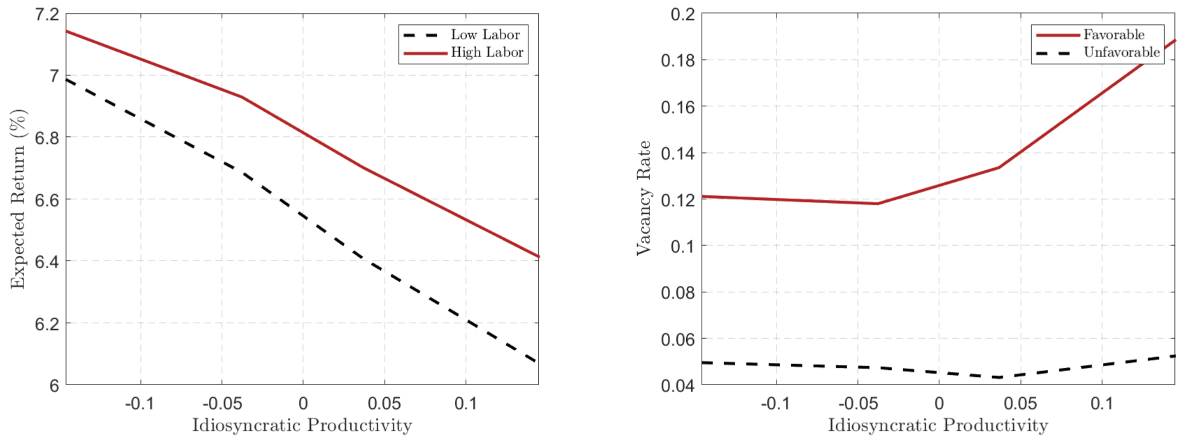
Notes: Figure 3 plots impulse-response functions to a one standard deviation negative aggregate TFP shock.

the relative smoothness of the risk-free rate in our setting is driven by countercyclical consumption volatility, which offsets the effects of low intertemporal elasticity of substitution (IES) (Chen, 2017; Smirnyagin and Tsyvinski, 2022). Figure A.2 in the Appendix illustrates that a given change in the aggregate stock price is associated with a larger change in aggregate consumption when surplus consumption S is low, as compared to when S is high. In other words, consumption is more volatile during bad aggregate times, thereby inducing a precautionary savings motive and increasing households' demand for a risk-free asset in downturns.[12] Additionally, the autocorrelation of the risk-free rate is high, while the autocorrelation of stock returns is low in our model; these moments were not targeted and are consistent with the U.S. data.

Impulse-Response Functions. Figure 3 plots the impulse-response functions to a one standard deviation negative aggregate TFP shock. Upon impact, aggregate output and consumption decline, followed by a gradual recovery. Firms post fewer vacancies, unemployment rises, and consequently, the vacancy-to-unemployment ratio falls on impact. Since household utility features a slow-moving habit stock (Equation 13), marginal utility increases by more than the decline in consumption. The resulting high volatility of marginal utility is crucial for generating equity premium.

[12]Precautionary savings motive was shown to play an important role in accounting for a persistent drop in the job finding rate during the financial crisis (Ravn and Sterk, 2017).

FIGURE 4: STOCK RETURNS, PRODUCTIVITY, AND VACANCY POSTING RATE



(A) Expected Returns and Id. Productivity

(B) Vacancy Posting Rate and Id. Productivity

Notes: Figure 4 contains two panels. Panel (A) plots expected stock returns against idiosyncratic productivity. The red solid line corresponds to large firms (above-median labor), and the black dashed line corresponds to small firms (below-median labor). Expected stock return for a firm with state (n,z) at time t is defined as $\mathbb{E}_t\left[\frac{v_{t+1}(n',z')}{v_t(n,z)-d_t(n,z)}\right]$, where $d_t(n,z) = y_t(n,z) - W_t n - AC(n,vc) - \kappa \times vc$. Panel (B) plots the vacancy rate against idiosyncratic productivity. The red solid line corresponds to firms operating under favorable labor market conditions, while the red dashed line represents firms in unfavorable labor markets.

5.5 Quantitative Results

In this section, we demonstrate that the quantitative general equilibrium model developed in Section 5 accounts for the empirical findings documented in the previous section. That is, we also show that the theoretical predictions derived from the simple partial equilibrium model carry over to the quantitative framework, which features endogenous market tightness and a vacancy filling rate.

Idiosyncratic Productivity, Returns, and Vacancy Rate. In the model, firms are heterogeneous along two dimensions: labor and idiosyncratic productivity. Firms with low idiosyncratic productivity and high labor stock are riskier, as they face frictions in adjusting their workforce and, thus, must continue paying wages despite low productivity. As a result, unproductive firms with high accumulated labor stocks are particularly exposed to aggregate productivity shocks and must offer higher expected returns to investors. Consistent with this intuition, Panel (A) of Figure 4 shows that expected stock returns decline sharply with idiosyncratic productivity. Differences in labor also contribute to the cross-sectional differences in returns, though to a lesser extent, as evidenced

Table 8: Predictive Regressions in the Model-Simulated Data

	Expected return				Future dividend			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Vacancy rate	-0.002	-0.008	-0.002	-0.008	0.316	0.663	0.315	0.660
Vacancy rate x Favorable		0.004		0.004		-0.143		-0.141
Favorable		0.001		0.001		-0.070		-0.069
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	N	N	Y	Y	N	N	Y	Y
R^2	0.615	0.797	0.617	0.799	0.425	0.455	0.431	0.461

Notes: Table 8 reports OLS estimates from regressions of expected returns (Columns (1)–(4)) and $t+1$ dividends (Columns (5)–(8)) on the current firm-level vacancy posting rate. The model period corresponds to one quarter. *Favorable* is a dummy variable that is equal to one for firms with a high vacancy-filling rate at time t, and zero otherwise. *Vacancy rate* is defined as the ratio of posted vacancies to labor. *Dividend* is computed as $d_t(n,z) = y_t(n,z) - W_t n - AC(n,vc) - \kappa \times vc$, normalized by firm-level labor n. Regressions include lagged idiosyncratic productivity as a control.

by the relatively small gap between returns for large firms (solid red line) and small firms (dashed black line). Intuitively, labor is a slowly moving state variable due to adjustment costs, whereas productivity evolves more rapidly and accounts for most of the variation in expected returns.

Panel (B) plots the average vacancy rate as a function of idiosyncratic productivity; the red solid and black dashed lines correspond to firms operating in favorable and unfavorable labor markets, respectively. We observe that the vacancy rate increases rapidly with productivity for firms in favorable labor market environments. In other words, under favorable labor market conditions (i.e., with a high vacancy-filling rate), differences in productivity are more readily translated into differences in vacancy postings. In contrast, under unfavorable conditions, differences in productivity must be much larger to justify the same observed difference in vacancy posting behavior.

Inspecting the Mechanism. We now explain why our model accounts for the empirical findings. First, a higher vacancy rate implies that the firm is more productive; and, as discussed above, higher productivity is associated with lower expected returns. Provided that cash flows increase in productivity, the model can also account for the positive relationship between vacancy posting and future cash flows.

Inverting the relationship between the vacancy-posting rate and productivity sheds light on why the predictive power of vacancy postings is muted in favorable labor markets. Under favorable conditions, the vacancy rate grows more rapidly in productivity. As a result, if we compare two firms with the same observed difference in vacancy rates, the implied difference in their productivity will be smaller under favorable conditions than under unfavorable ones. In other words, to justify the same gap in observed vacancy rates, the gap in idiosyncratic productivity must be larger in unfavorable labor markets. This, in turn, leads to a larger gap in expected returns and future cash flows. Thus, the vacancy rate is a stronger predictor of returns and cash flows under unfavorable labor markets conditions, consistent with our empirical findings.

We confirm the above logic through model simulations. Specifically, we simulate a panel of firms and estimate OLS regressions of expected returns and future dividends on current firm-level vacancy posting rates (Table 8). We find that, on average, the relationship between vacancy posting behavior and expected returns is negative (Column (1)). However, as shown in Column (2), this average masks substantial heterogeneity: firms operating under unfavorable labor market conditions–those that face a lower vacancy-filling rate–exhibit a much stronger negative association between vacancy postings and returns. These results are robust to including both time and firm fixed effects (Column (4)).

In Columns (5)–(8), we study the relationship between vacancy postings and future firm dividends. The left-hand side variable is the logarithm of dividends normalized by firm's labor. On average, the relationship is positive: a higher vacancy rate at time t is associated with a higher dividend in quarter $t+1$. Column (6) shows that this relationship is the strongest for firms operating under unfavorable labor market conditions, while it is quantitatively weaker for firms in favorable labor markets. Columns (7)–(8) demonstrate that the inclusion of firm fixed effects does not materially alter these conclusions.

6 Conclusion

This paper studies the relationship between firms' labor market decisions and their expected returns and future cash flows. Using a dataset that covers the near-universe of online job postings in the U.S., we show that vacancy posting rates are negatively associated with expected returns and positively associated with expected cash flows. These relationships are much stronger for firms operating under less favorable labor market conditions, highlighting the importance of firm-specific labor market environments in understanding asset prices.

We develop a general equilibrium production-based asset pricing model with heterogeneous firms and firm-specific labor market conditions. The model matches central business cycle and aggregate asset pricing moments. The model accounts for our empirical results: the vacancy rate positively predicts future cash flows and negatively predicts expected returns. At the same time, the predictive power of the vacancy rate is weaker for firms operating under favorable labor market conditions.

Acknowledgments

We thank Hang Bai, Nick Barberis, Jaroslav Borovicka, Kent Daniel, Steven Davis, Jan Eeckhout, Stefano Giglio, William Goetzmann, Michael Gofman, Bryan Kelly, Toomas Laarits, Jun Li (discussant), Ernest Liu, Sydney Ludvigson, Ding Luo, Ben Matthies, Andrew Metrick, Alan Moreira, Giuseppe Moscarini, Tobias Moskowitz, Tyler Muir, Stefan Nagel, Michael Peters, Anton Petukhov (discussant), Scott Richardson, Gill Segal, Jinfei Sheng, Vincent Sterk, Aleh Tsyvinski, Kaushik Vasudevan, Jessie Wang, Xiaofei Zhao (discussant), as well as seminar participants at the Blackrock Applied Research Conference, Northern Finance Association, SFS Cavalcade, Trans-Atlantic Doctoral Conference, University of Chicago, University of Colorado at Boulder, University of Maryland, University of Rochester, University of Texas at Austin, University of Washington Seattle, and Yale University for helpful comments. We thank Bledi Taska and Will Markow for providing us with the Burning Glass Technologies data. We also thank the International Center for Finance at Yale School of Management for financial support.

References

Algan, Yann, Olivier Allais, and Wouter J Den Haan, "Solving heterogeneous-agent models with parameterized cross-sectional distributions," *Journal of Economic Dynamics and Control*, 2008, *32* (3), 875–908.

Antweiler, Werner and Murray Frank, "Is all that talk just noise? The information content of internet stock message boards," *The Journal of Finance*, 2004, *59* (3), 1259–1294.

Bai, Hang, "Unemployment and credit risk," *Journal of Financial Economics*, 2021, *142* (1), 127–145.

_ **and Lu Zhang**, "Searching for the equity premium," *Journal of Financial Economics*, 2022, *143* (2), 897–926.

Baydur, Ismail and Toshihiko Mukoyama, “Job duration and match characteristics over the business cycle,” *Review of Economic Dynamics*, 2020, *37*, 33–53.

Belo, Frederico, Andres Donangelo, Xiaoji Lin, and Ding Luo, “Labor hiring, aggregate dividends, and return predictability in the time series,” *Working Paper*, 2018.

_ , Xiaoji Lin, and Santiago Bazdresch, “Labor hiring, investment, and stock return predictability in the cross section,” *Journal of Political Economy*, 2014, *122* (1), 129–177.

Borovicka, Jaroslav and Katarına Borovicková, “Risk premia and unemployment fluctuations,” *Working Paper*, 2018.

Campbell, John, “Intertemporal asset pricing without consumption data,” *American Economic Review*, 1993.

_ and John Cochrane, “By force of habit: A consumption-based explanation of aggregate stock market behavior,” *Journal of Political Economy*, 1999, *107* (2), 205–251.

_ and Robert Shiller, “The dividend-price ratio and expectations of future dividends and discount factors,” *Review of Financial Studies*, 1988, *1* (3), 195–228.

Chen, Andrew Y, “External habit in a production economy: A model of asset prices and consumption volatility risk,” *The Review of Financial Studies*, 2017, *30* (8), 2890–2932.

Chen, Huafeng Jason, Marcin Kacperczyk, and Hernan Ortiz-Molina, “Labor unions, operating flexibility, and the cost of equity,” *Journal of Financial and Quantitative Analysis*, 2011, *46* (1), 25–58.

Chen, Long and Xinlei Zhao, “Return decomposition,” *Review of Financial Studies*, 2009, *22* (12), 5213–5249.

Cochrane, John H, “Production-based asset pricing and the link between stock returns and economic fluctuations,” *The Journal of Finance*, 1991, *46* (1), 209–237.

_ , “A cross-sectional test of an investment-based asset pricing model,” *Journal of Political Economy*, 1996, *104* (3), 572–621.

Cooley, Thomas F and Edward C Prescott, “Economic growth and business cycles,” *Frontiers of business cycle research*, 1995, *1.*

Da, Zhi, Joseph Engelberg, and Pengjie Gao, “In search of attention,” *The Journal of Finance*, 2011, *66* (5), 1461–1499.

Davis, Steven J, R Jason Faberman, and John C Haltiwanger, “The establishment-level behavior of vacancies and hiring,” *The Quarterly Journal of Economics*, 2013, *128* (2), 581–622.

Diamond, Peter, “Wage determination and efficiency in search equilibrium,” *Review of Economic Studies*, 1982, *49* (2), 217–227.

Donangelo, Andres, “Labor mobility: Implications for asset pricing,” *The Journal of Finance*, 2014, *69* (3), 1321–1346.

_ , Francois Gourio, Matthias Kehrig, and Miguel Palacios, “The cross-section of labor leverage and equity returns,” *Journal of Financial Economics*, 2018.

Dougal, Casey, Christopher A Parsons, and Sheridan Titman, “Urban vibrancy and corporate growth,” *The Journal of Finance*, 2015, *70* (1), 163–210.

Eisfeldt, Andrea L and Dimitris Papanikolaou, "Organization capital and the cross-section of expected returns," *The Journal of Finance*, 2013, *68* (4), 1365–1406.

Engelberg, Joseph, Arzu Ozoguz, and Sean Wang, "Know thy neighbor: Industry clusters, information spillovers and market efficiency," *Journal of Financial and Quantitative Analysis*, 2018.

Fallick, Bruce and Charles A Fleischman, "Employer-to-employer flows in the U.S. labor market: The complete picture of gross worker flows," *Working Paper*, 2004.

Fama, Eugene and James MacBeth, "Risk, return, and equilibrium: Empirical tests," *Journal of Political Economy*, 1973, *81* (3), 607–636.

_ and Kenneth French, "Dividend yields and expected stock returns," *Journal of Financial Economics*, 1988, *22* (1), 3–25.

Fama, Eugene F and Kenneth R French, "Forecasting profitability and earnings," *The Journal of Business*, 2000, *73* (2), 161–175.

_ and _ , "Profitability, investment and average returns," *Journal of Financial Economics*, 2006, *82* (3), 491–518.

Favilukis, Jack and Xiaoji Lin, "Wage rigidity: A quantitative solution to several asset pricing puzzles," *Review of Financial Studies*, 2015, *29* (1), 148–192.

Gebhardt, William R, Charles MC Lee, and Bhaskaran Swaminathan, "Toward an implied cost of capital," *Journal of Accounting Research*, 2001, *39* (1), 135–176.

Hall, Robert, "High discounts and high unemployment," *American Economic Review*, 2017, *107* (2), 305–330.

Hodrick, Robert J, "Dividend yields and expected stock returns: Alternative procedures for inference and measurement," *Review of Financial Studies*, 1992, *5* (3), 357–386.

Hou, Kewei, Mathijs A Van Dijk, and Yinglei Zhang, "The implied cost of capital: A new approach," *Journal of Accounting and Economics*, 2012, *53* (3), 504–526.

İmrohoroğlu, Ayşe and Şelale Tüzel, "Firm-level productivity, risk, and return," *Management Science*, 2014, *60* (8), 2073–2090.

Jermann, Urban J, "Asset pricing in production economies," *Journal of Monetary Economics*, 1998, *41* (2), 257–275.

Kehoe, Patrick, Elena Pastorino, and Virgiliu Midrigan, "Debt constraints and employment," *Journal of Political Economy*, 2018.

Khan, Aubhik and Julia K Thomas, "Idiosyncratic shocks and the role of nonconvexities in plant and aggregate investment dynamics," *Econometrica*, 2008, *76* (2), 395–436.

Kilic, Mete and Jessica Wachter, "Risk, unemployment, and the stock market: A rare-event-based explanation of labor market volatility," *Review of Financial Studies*, 2018.

Korniotis, George M and Alok Kumar, "State-level business cycles and local return predictability," *The Journal of Finance*, 2013, *68* (3), 1037–1096.

Krusell, Per, Toshihiko Mukoyama, Richard Rogerson, and Ayşegül Şahin, "Gross worker flows over the business cycle," *American Economic Review*, 2017, *107* (11), 3447–76.

— , — , — , **and** — , "Gross worker flows and fluctuations in the aggregate labor market," *Review of Economic Dynamics*, 2020, *37*, S205–S226.

Kuehn, Lars-Alexander, Mikhail Simutin, and Jessie Jiaxu Wang, "A labor capital asset pricing model," *The Journal of Finance*, 2017.

Kwan, Alan and Yukun Liu, "Labor market power and firm financial flexibility," *Working Paper*, 2018.

Lettau, Martin and Sydney Ludvigson, "Consumption, aggregate wealth, and expected stock returns," *The Journal of Finance*, 2001, *56* (3), 815–849.

Liu, Yukun and Xi Wu, "Labor links, comovement, and predictable returns," *Journal of Financial and Quantitative Analysis*, 2025.

Luo, Ding and Jincheng Tong, "Search Intensity and Asset Prices," *Available at SSRN 4287343*, 2024.

Lustig, Hanno and Stijn Van Nieuwerburgh, "Housing collateral, consumption insurance, and risk premia: An empirical perspective," *The Journal of Finance*, 2005, *60* (3), 1167–1219.

Melcangi, Davide and Vincent Sterk, "Stock market participation, inequality, and monetary policy," *The Review of Economic Studies*, 2024.

Miranda, Mario J and Paul L Fackler, *Applied computational economics and finance*, MIT press, 2004.

Mortensen, Dale and Christopher Pissarides, "Job creation and job destruction in the theory of unemployment," *Review of Economic Studies*, 1994, *61* (3), 397–415.

Petrosky-Nadeau, Nicolas, Lu Zhang, and Lars-Alexander Kuehn, "Endogenous disasters," *American Economic Review*, 2018.

Philippon, Thomas, "The bond market's q," *The Quarterly Journal of Economics*, 2009, *124* (3), 1011–1056.

Pirinsky, Christo and Qinghai Wang, "Does corporate headquarters location matter for stock returns?," *The Journal of Finance*, 2006, *61* (4), 1991–2015.

Ravn, Morten O. and Vincent Sterk, "Job uncertainty and deep recessions," *Journal of Monetary Economics*, 2017, *90*, 125–141.

Rudanko, Leena, "Aggregate and idiosyncratic risk in a frictional labor market," *American Economic Review*, 2011, *101* (6), 2823–2843.

Schmidt, Lawrence, "Climbing and falling off the ladder: Asset pricing implications of labor market event risk," *Working Paper*, 2016.

Sheng, Jinfei, "Asset pricing in the information age: Employee expectations and stock returns," *Review of Asset Pricing Studies*, 2025.

Sloan, Richard G, "Do stock prices fully reflect information in accruals and cash flows about future earnings?," *The Accounting Review*, 1996, *71* (3), 289–315.

Smirnyagin, Vladimir and Aleh Tsyvinski, "Macroeconomic and asset pricing effects of supply chain disasters," *SSRN working paper 4223600*, 2022.

Stambaugh, Robert, "Predictive regressions," *Journal of Financial Economics*, 1999, *54* (3), 375–421.

Stock, James and Mark Watson, "A simple estimator of cointegrating vectors in higher order integrated systems," *Econometrica: Journal of the Econometric Society*, 1993, pp. 783–820.

Stole, Lars and Jeffrey Zwiebel, "Organizational design and technology choice under intrafirm bargaining," *American Economic Review*, 1996, *86* (1), 195–222.

Tang, Yue, Jin Wu, and Lu Zhang, "Do anomalies exist ex ante?," *Review of Finance*, 2013, *18* (3), 843–875.

Tuzel, Selale and Miao Ben Zhang, "Local risk, local factors, and asset prices," *The Journal of Finance*, 2017, *72* (1), 325–370.

Welch, Ivo and Amit Goyal, "A comprehensive look at the empirical performance of equity premium prediction," *Review of Financial Studies*, 2007, *21* (4), 1455–1508.

Winberry, Thomas, "A method for solving and estimating heterogeneous agent macro models," *Quantitative Economics*, 2018, *9* (3), 1123–1151.

_ , "Lumpy investment, business cycles, and stimulus policy," *American Economic Review*, 2021, *111*, 364–396.

Young, Eric R, "Solving the incomplete markets model with aggregate uncertainty using the Krusell–Smith algorithm and non-stochastic simulations," *Journal of Economic Dynamics and Control*, 2010, *34* (1), 36–41.

Zhang, Lu, "The value premium," *The Journal of Finance*, 2005, *60* (1), 67–103.

Zhang, Miao Ben, "Labor-technology substitution: Implications for asset pricing," *The Journal of Finance*, 2018.

Appendix

A Graphs & Tables

Table A.1: Portfolio Results

Portfolio Returns					
	XRet	CAPM	3-Fac	4-Fac	5-Fac
Bottom	1.39	0.07	0.36	0.42	0.48
	(2.79)	(0.30)	(2.38)	(2.82)	(3.59)
2	1.14	-0.12	0.13	0.21	0.14
	(2.46)	(-0.61)	(1.15)	(2.23)	(1.24)
3	1.04	-0.29	-0.08	-0.02	-0.09
	(2.17)	(-1.65)	(-0.74)	(-0.18)	(-0.86)
4	1.14	-0.20	0.02	0.04	-0.00
	(2.39)	(-1.19)	(0.26)	(0.45)	(0.03)
Top	1.03	-0.26	0.01	0.03	0.03
	(2.19)	(-1.33)	(0.14)	(0.33)	(0.38)
Bottom - Top	0.37	0.33	0.35	0.39	0.45
	(2.41)	(2.01)	(2.03)	(2.06)	(3.30)

Notes: Table A.1 reports mean portfolio returns (in percentage) and alphas sorted by *AbPost*. The table reports time-series averages of monthly equal-weighted industry portfolio excess returns, along with alphas adjusted for the Fama-French 3-factor model, the Carhart 4-factor model, and the Fama-French 5-factor model. Newey-West t-statistics are in parentheses.

Table A.2: Industry-Level Portfolio Results

Portfolio Returns					
	XRet	CAPM	3-Fac	4-Fac	5-Fac
Bottom	1.26	0.37	0.37	0.43	0.37
	(3.24)	(1.59)	(1.65)	(2.01)	(1.60)
Middle	0.90	0.01	0.00	0.01	-0.01
	(2.75)	(0.08)	(0.00)	(0.10)	(-0.16)
Top	0.64	-0.21	-0.24	-0.25	-0.23
	(1.85)	(-1.26)	(-1.49)	(-1.56)	(-1.41)
Bottom - Top	0.62	0.58	0.61	0.68	0.61
	(2.32)	(2.15)	(2.27)	(2.67)	(2.19)

Notes: Table A.2 reports mean portfolio returns and alphas based on *AbPost* at the industry level. The analysis covers sixteen 2-digit NAICS industries. In each quarter, the top portfolio comprises the two industries with the highest *AbPost* values, while the bottom portfolio includes the two industries with the lowest *AbPost* values. The remaining industries are grouped into the middle portfolio. Industry returns are value-weighted. The table reports time-series averages of monthly equal-weighted industry portfolio excess returns, as well as alphas adjusted for the Fama-French 3-factor model, the Carhart 4-factor model, and the Fama-French 5-factor model. Data spans the time period from the beginning of 2003 to the end of 2017. Newey-West t-statistics are in parentheses.

Table A.3: Forecasting Aggregate Stock Market Return with Vacancy Posting Rate

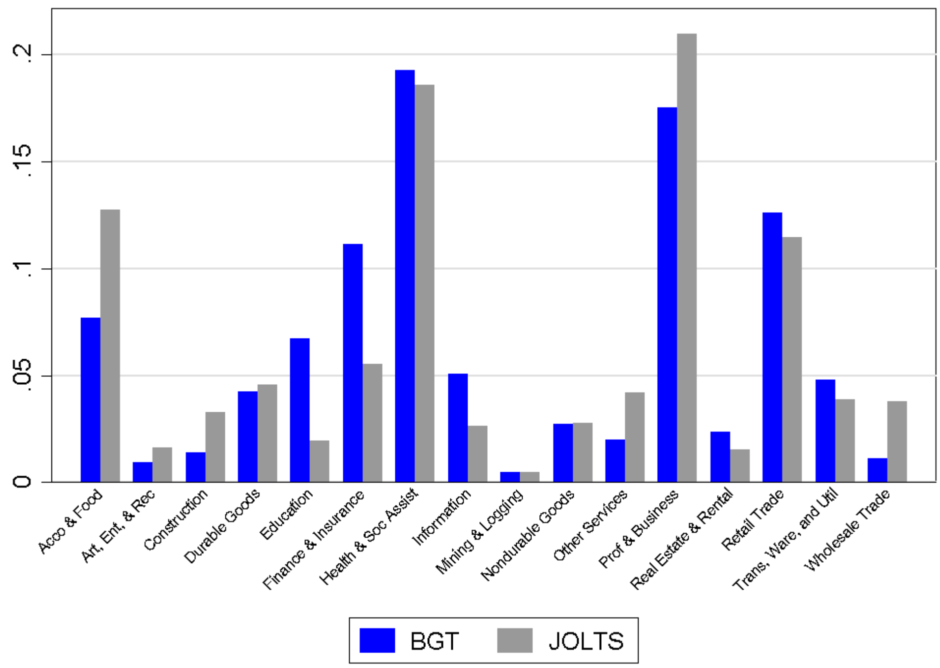
(Percentage)		β	t-stat	Adj. R^2
t+1	CRSP	-3.00^{**}	-2.67	0.02
t+1	S&P 500	-2.79^{**}	-2.56	0.02
t+2	CRSP	-2.63^{**}	-2.46	0.02
t+2	S&P 500	-2.48^{**}	-2.42	0.02

Notes: Table A.3 reports OLS estimation results for regressions of one-period-ahead log excess stock returns on the aggregate vacancy posting rate (in percent). Newey–West adjusted t-statistics are reported. Data frequency is quarterly. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A.4: Parameter Values

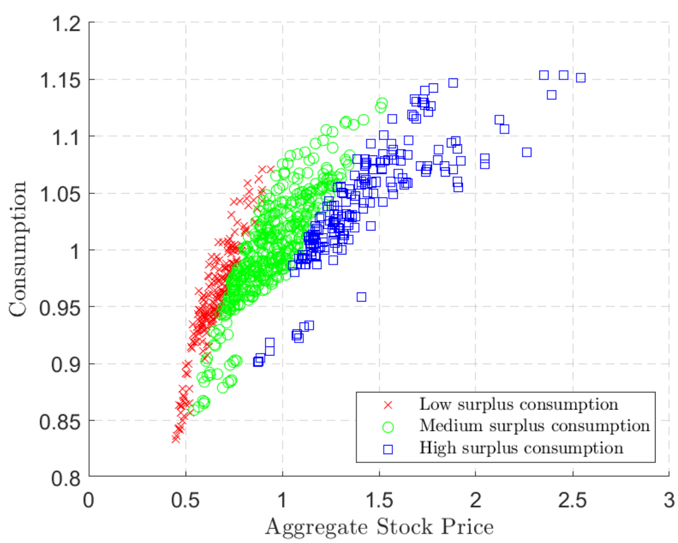
Parameter	**Description**	**Value**	**Target/Source**	**Data**	**Model**
s	Separation rate	0.120	Davis, Faberman and Haltiwanger (2013)		
ν	Labor share	0.670			
σ	Curvature of utility function	2	Campbell and Cochrane (1999)		
ι	Curvature of matching function	1.250	Petrosky-Nadeau, Zhang and Kuehn (2018)		
λ_H	Habit sensitivity	$\frac{1}{\bar{S}}-1$	Chen (2017)		
η	Bargaining power	0.040	Petrosky-Nadeau, Zhang and Kuehn (2018)		
b	Unemployment benefit	0.850	Rudanko (2011)		
ρ_z	Persistence of idiosyncratic AR(1)	0.900			
σ_z	Std of idiosyncratic AR(1)	0.050			
β	Discount factor	0.988	90-day T-bill return (annualized)	0.89	0.78
κ	Vacancy posting cost	0.600	Quarterly unemployment volatility	0.19	0.16
Δ	Favorable/unfavorable vac. filling rate gap	0.190	$P10\left[\frac{vc}{n}\right]$	0.00	0.02
p^F	Probability of favorable	0.720	$P90\left[\frac{vc}{n}\right]$	0.17	0.19
φ	Quadratic adj. cost	1.100	$\sigma\left[\frac{vc}{n}\right]$	0.19	0.10
$\bar{S}$	St. state suplus consumption	0.090	Mean Sharpe ratio	0.40	0.30
ρ_Z	Persistence of aggregate TFP	0.950	Persistence of output	0.90	0.92
ρ_H	Habit persistence	0.900	Persistence of price-div ratio	0.85	0.90
σ_Z	Std of aggregate TFP	0.013	$\sigma(Y)$	1.80	1.98

FIGURE A.1: INDUSTRY COMPOSITION OF BURNING GLASS TECHNOLOGIES AND JOLTS



Notes: Figure A.1 compares the industry composition of the Burning Glass Technologies sample with that of the JOLTS sample.

FIGURE A.2: COUNTERCYCLICAL CONSUMPTION VOLATILITY



Notes: Figure A.2 plots aggregate consumption as a function of the aggregate stock price. Red crosses, green circles and blue squares correspond to periods with low, medium and high suplus consumption.

B Variable Definitions

Variable	Description
AbPost	Quarterly vacancy posting rate – measured as the vacancy posting to total employees minus its past eight-quarter moving average.
Size	Quarterly market capitalization at the end of last month measured (logarithm).
BM	Quarterly ratio of total book value of equity to total market capitalization.
MOM	Cumulative return from past twelfth to past second month.
Prof	Quarterly gross profitability over lagged total assets.
HN	Annual employee growth rate as defined in Belo, Lin and Bazdresch (2014).
IK	Capital expenditure over total assets.
R&D	R&D expenditure over total assets.
$\mathbf{1}_{Power>Median}$	An indicator variable for firms with above median relative labor market concentration index as in Kwan and Liu (2018) in a period.
$\mathbf{1}_{Skill<Median}$	An indicator variable for firms with below median high-skill job requirement ratio in a period.
$\mathbf{1}_{Yield>Median}$	An indicator variable for firms in sectors with above median vacancy yield ratio in a period.
ROA	Income before extraordinary items to total assets.
NegE	An indicator variable for firms with negative earnings.
Div	The dividend paid in the previous year divided by total assets.
DDiv	An indicator variable for dividend paying firms.
AC	Firm absolute accruals scaled by assets as in Sloan (1996).
ev	The employee valuation ratio as defined in the text.
ik (%)	The investment rate as in Philippon (2009).
dp	The natural logarithm of the dividend-to-price ratio.
ep	The natural logarithm of the earning-to-price ratio.
cay	The consumption-to-wealth ratio as in Lettau and Ludvigson (2001), from Sydney Ludvisgon's website.
tbill	The relative bill rate–measured as the difference between the three-month treasury bill rate and its four-quarter backward moving average .
q	Aggregate Tobin's q as in Philippon (2009).
Vacancy Posting Rate (%)	Aggregate vacancy posting number over total employment.
Hiring Rate (%)	Aggregate number of hires over total employment.
Separation Rate (%)	Aggregate number of separations over total employment.
Initial Claim Rate (%)	Aggregate number of initial claims for unemployment insurance over total employment as in Schmidt (2016).
EE Rate (%)	Employer-to-employer transition rate as in Fallick and Fleischman (2004).

Online Appendix

"Labor-Based Asset Pricing"

by Yukun Liu and Vladimir Smirnyagin

Table of Contents for Online Appendix

Appendix C: Empirical Appendix

C.1 Aggregate Return Predictability of the Vacancy Posting Rate and the Employee Valuation Ratio

Consistent with the firm-level results, vacancy posting rates significantly and negatively predict future aggregate equity returns. Table A.3 reports the return predictability results for aggregate vacancy posting rates over the past 70 years. Vacancy posting rates negatively predict future aggregate excess stock returns, whether measured using S&P 500 index returns or CRSP stock market returns. The adjusted R^2 values are 2 percent for both one-quarter and two-quarter ahead returns.

While the aggregate vacancy posting rate exhibits significant predictive power for future returns, we later show that this power is subsumed by the employee valuation ratio–a measure that incorporates both aggregate labor demand and labor market conditions.

C.1.1 The Employee Valuation Ratio

In this section, we introduce a new measure–the employee valuation ratio. Consider a representative firm that has access to a production technology, whereby labor and physical capital are separable. From the perspective of employers, the value of employees derives from their future cash flow. That is, employers evaluate the value of employees in the same way they evaluate any generic financial asset. Under the assumption that labor and capital enter the production function separately, the value of employees from the employer's standpoint is given by:

$$V_t^{emp} = \mathbb{E}_t\left[\sum_{k=1}^{\infty} M_{t\to t+k}^{emp} E_{t+k} \Lambda_{t\to t+k}\right] = \mathbb{E}_t\left[M_{t+1}^{emp}\left(V_{t+1}^{emp} + E_{t+1}\right)\Lambda_{t+1}\right],$$

where V_t^{emp} is the value of employees at time t, E_t is the cash flow generated by employees and shared by the firm at time t, $M_{t\to t+k}^{emp}$ is the stochastic discount factor from t to $t+k$, and $\Lambda_{t\to t+k}$ is the employee retention rate from t to $t+k$.

We define the realized one-period employee return, R^{emp}, similar to that of a generic asset:

$$R_{t+1}^{emp} \equiv \frac{V_{t+1}^{emp} + E_{t+1}}{V_t^{emp}} \Lambda_{t+1}. \tag{C.1}$$

The ratio E/V^{emp} is referred to as the employee valuation ratio.

Let $r^{emp} \equiv \log(1+R^{emp})$. Throughout this section, we use lowercase letters to denote natural logarithms. If the employee valuation ratio, E/V^{emp}, is stationary, then Equation (C.1) can be approximated using a first-order Taylor expansion around the employee valuation ratio, yielding a linear relationship between r^{emp}, v, e, and λ: $r^{emp}_{t+1} \approx \Delta v_{t+1} + \kappa + (1-\rho)(e_{t+1} - v_{t+1}) + \lambda_{t+1}$, where $\rho = \frac{1}{\exp(\mu_{e-v})+1}$ and $\kappa = -\log(\rho) - (1-\rho)\log\left(\frac{1}{\rho} - 1\right)$.

Solving this equation forward and imposing the no-bubble condition $\lim_{i\to\infty} \rho^i (e_{t+i} - v_{t+i}) = 0$, the employee valuation ratio can be expressed as:

$$e_t - v_t^{emp} = \frac{\kappa}{\rho - 1} + \sum_{i\geq 0} \rho^i \left[(r^{emp}_{t+1+i} - r^f_{t+1+i}) - \Delta e_{t+1+i} - \lambda_{t+1+i} + r^f_{t+1+i} \right]. \tag{C.2}$$

This equation holds as an accounting identity, and therefore holds ex post. Taking conditional expectations on both sides yields:

$$e_t - v_t^{emp} = \frac{\kappa}{\rho - 1} + \mathbb{E}_t \sum_{i\geq 0} \rho^i \left[\left(r^{emp}_{t+1+i} - r^f_{t+1+i} \right) - \Delta e_{t+1+i} - \lambda_{t+1+i} + r^f_{t+1+i} \right]. \tag{C.3}$$

Equation (C.3) shows that, if the employee valuation ratio is not constant, it should forecast future excess labor market returns, cash flow growth, retention rates, or risk-free rates. If none of these four variables are forecastable, then the employee valuation ratio would be constant.

It is instructive to compare Equation (C.3) with the decomposition of the log dividend-price ratio. In their seminal paper, Campbell and Shiller (1988) show that the log dividend-price ratio can be approximated as follows:

$$d_t - p_t = \frac{\kappa_{dp}}{\rho_{dp} - 1} + \sum_{j\geq 0} \rho^j_{dp} \left[\left(r_{t+1+j} - r^f_{t+1+j} \right) - \Delta d_{t+1+j} + r^f_{t+1+j} \right], \tag{C.4}$$

where d_t and p_t are the log dividend and log price, respectively, and ρ_{dp} and κ_{dp} are constants. Equation (C.4) is derived by taking the first-order Taylor expansion of log stock returns around the dividend-price ratio. It implies that when the dividend-price ratio is high, agents must be expecting either high future excess returns, low dividend growth, or high risk-free rates.

There is a clear similarity between Equation (C.2) and Equation (C.4). Both equations hold ex ante and ex post. When the employee valuation ratio is high, agents must be expecting high excess labor market returns, low cash flow growth, low retention rates, or high risk-free rates. Expanding on this analogy, the cash flow component plays a role similar to dividends generated by a stock, and the term λ represents the fraction of employees that stay with their employers; it can be thought of being 1 in the context of the stock market.

The framework above requires a way to measure the employee value, which is not directly observable. Labor search literature provides guidance on how to approximate this value. A firm's incentive to recruit a new employee is governed by the present value of the difference between the marginal benefit the employee brings and the compensation the worker receives. In equilibrium, assuming free entry into the vacancy posting market, the value of an employee equals the cost of recruitment.

The cost of recruitment depends on aggregate labor market conditions, which can be proxied by the number of vacancies, and the flow of hiring. Labor search-and-matching literature suggests the following approximation for the aggregate cost of recruitment: $\frac{\kappa A_t}{Q_t}$, where Q_t is the vacancy-filling rate (i.e., the ratio of hires to vacancies), A_t is labor productivity at time t, and κ is a constant. The equilibrium condition that equates the cost and benefit of recruitment is $\frac{\kappa A_t}{Q_t} = V_t^{emp}$. Taking logarithms of both sides yields $v_t = \log(\kappa) + (a_t - q_t)$. Substituting this expression into Equation (C.2) and dropping constant terms, the equation can be rewritten using observable variables as follows:

$$e_t - (a_t - q_t) = \mathbb{E}_t \sum_{i \geq 0} \rho^i \left[\left(r^{emp}_{t+1+i} - r^f_{t+1+i} \right) - \Delta e_{t+1+i} - \lambda_{t+1+i} + r^f_{t+1+i} \right]. \tag{C.5}$$

Instead of imposing a fixed relationship between e_t and $(a_t - q_t)$, we follow Lettau and Ludvigson (2001) and Lustig and Van Nieuwerburgh (2005) and estimate a cointegration process between these variables. Equation (C.5) then becomes:

$$e_t - w(a_t - q_t) = \mathbb{E}_t \sum_{i \geq 0} \rho^i \left[\left(r^{emp}_{t+1+i} - r^f_{t+1+i} \right) - \Delta e_{t+1+i} - \lambda_{t+1+i} + r^f_{t+1+i} \right]. \tag{C.6}$$

Equation (C.6) expresses the employee valuation ratio entirely in terms of observables, making it estimable from historical data. We further relate employee returns to returns on stocks and corporate bonds. Assuming all firms are tradable and labor is the only non-financial asset, aggregate employee returns can be equated to aggregate firm returns. We assume that the conditional expected employee return is a linear combination of expected stock and bond returns:

$$\mathbb{E}_t r_{t+1}^{emp} = \phi \mathbb{E}_t r_{t+1}^{s} + (1-\phi)\mathbb{E}_t r_{t+1}^{b}.$$

We impose the assumption on conditional expectations, and do not require $r_{t+1}^{emp} = \phi r_{t+1}^{s} + (1-\phi) r_{t+1}^{b}$ to hold pointwise.

Substituting this into Equation (C.6) and dropping constant terms, we obtain:

$$e_t - w(a_t - q_t) = \mathbb{E}_t \sum_{i \geq 0} \rho^i \left[\left(\phi r_{t+1+i}^{s} + (1-\phi) r_{t+1+i}^{b} - r_{t+1+i}^{f} \right) - \Delta e_{t+1+i} - \lambda_{t+1+i} + r_{t+1+i}^{f} \right]. \tag{C.7}$$

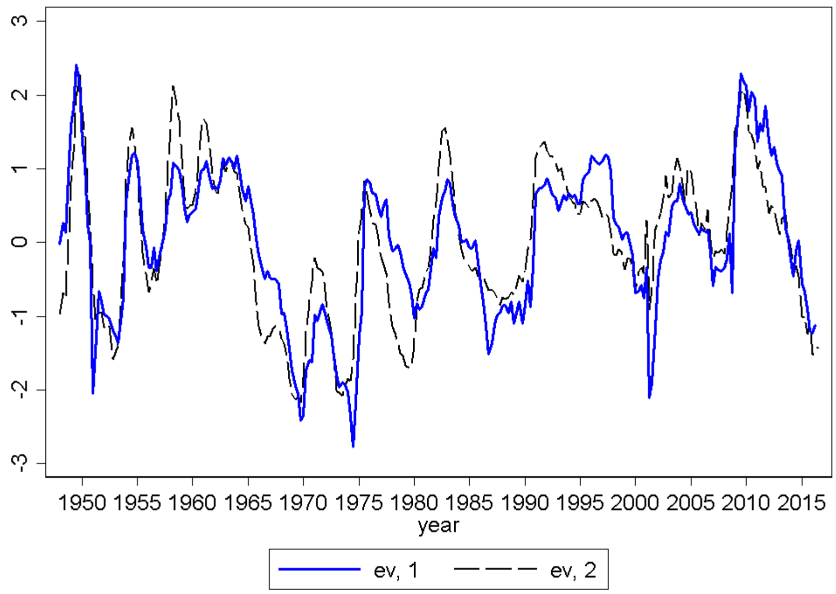
This equation motivates our empirical investigation of whether the employee valuation ratio can predict aggregate stock and corporate bond market returns.

Construction of the Employee Valuation Ratio. In this section, we describe the construction of the *employee valuation ratio*, defined as the ratio between cash flow and employee value. We use two data series to measure the cash flow generated by an employee and shared by the firm (E): (1) real non-farm business corporate profit after tax per employee, and (2) real non-farm business output minus labor compensation per employee. We denote the first series as E^1 and the second as E^2. Output A is measured as real non-farm business output per employee. The vacancy-filling rate Q is defined as the ratio of the flow of hiring to the number of vacancies.

Prior to 2001, vacancy posting data are obtained from the Help-Wanted Index, and hiring is calculated as the job-finding probability multiplied by the number of unemployed workers. After 2001, data on vacancies, hiring, and separations are sourced from JOLTS. The job-finding probability and separation rate before 2001 are obtained from Robert Shimer's website. The retention rate is computed as one minus the separation rate.

The logarithm of the real cash flow per employee (e) and the logarithm of the employee value ($a-q$) are nonstationary. According to the augmented Dickey-Fuller test, the null hypothesis of a unit root cannot be rejected at the 5 percent significance level for both series. Following Stock and Watson (1993), Lettau and Ludvigson (2001), and Lustig and Van Nieuwerburgh (2005), we employ a method that generates optimal estimates of the cointegrating parameters. Specifically, we use a dynamic least squares (DLS) technique, which specifies a single-equation model of the

FIGURE C.1: EMPLOYEE VALUATION RATIO



Notes: Figure C.1 plots the time-series of the two employee valuation ratios. ev^1 in blue and ev^2 in black. Data spans the time period from 1948 to 2016.

following form:

$$e_t = \alpha + \beta (a_t - q_t) + \sum_{i=-k}^{k} \beta' \Delta (a_{t-i} - q_{t-i}) + \varepsilon_t. \tag{C.8}$$

We estimate Equation (C.8), and the methodology provides consistent estimates of the cointegrating parameter β. We implement this estimation using ten lead and lag first differences, based on quarterly data from 1948Q1 to 2016Q4. Including lead and lag first differences delivers similar results. The first estimation, denoted ev^1, uses real non-farm business corporate profit after tax per employee, while the second estimation, ev^2, is based on real non-farm business output minus labor compensation per employee.

Additionally, we construct the employee return, r^{emp}, based on Definition C.1.[13] The time-series data are quarterly and span the period from 1948Q1 to 2016Q4. Unless otherwise specified, we use ev^1 for our tests, and refer to it simply as ev.

Figure C.1 plots the standardized versions of ev^1 and ev^2 over time in a single graph. Table C.4 in the Appendix reports the summary statistics for these variables.

[13] We rescale the level of E_t so that the mean of r^{emp} matches the corresponding stock market return.

C.1.2 Decomposition

Regressing the weighted long-run variables on the employee valuation ratio gives:

$$\sum_{i=1}^{H} \rho^{i-1} y_i = \alpha_y^{(H)} + \beta_y^{(H)} ev_t + \varepsilon_{t+H}^{y}$$

and

$$ev_{t+H} = \alpha_{ev}^{(H)} + \beta_{ev}^{(H)} ev_t + \varepsilon_{t+H}^{ev}, \tag{C.9}$$

where y is one of rx^{emp}, Δe, λ, and r^f. The linearized present value identity (C.6) implies that these long-run regression coefficients have to add up to one:

$$\beta_{r^e}^{(H)} - \beta_{\Delta z}^{(H)} - \beta_{\lambda}^{(H)} + \beta_{r^f}^{(H)} + \rho^H \beta_{ev}^{(H)} \approx 1. \tag{C.10}$$

Equation (C.10) highlights an important relationship. The ev ratio would not vary if we lived in an i.i.d. world. Since the ev ratio varies a lot in the data, as can be seen in Figure C.1, it must forecast excess labor market returns, cash flow growths, retention rates, risk-free rates or the bubble term. Equation (C.10) also provides a way to empirically test the driving forces of the employee valuation ratio.

We estimate both a one-quarter-ahead regression and a weighted long-run (20-quarters ahead) regression. We report the coefficient estimates, Newey–West adjusted t-statistics, and adjusted R^2 values in Panel A of Table C.1. For both the one-quarter-ahead and the weighted long-run regressions, we find economically large and statistically significant coefficient estimates when forecasting excess employee returns. In contrast, the coefficient estimates for forecasting cash flow growth are not statistically significant in both specifications.

Panel C of Table C.1 reports the long-run coefficients. We take these results as evidence that all the variation in the employee valuation ratio corresponds to the variation in expected excess employee returns.

In the Appendix C.2, we complement the direct decomposition approach described above with a VAR-based decomposition in the spirit of Campbell and Shiller (1988). The results from the VAR decomposition are qualitatively similar: variation in the risk premia accounts for approximately 100 percent of the movements in the employee valuation ratio.

Table C.1: Direct Decomposition

Panel A: Next Period Predictive Regression

	rx^{emp}_{t+1}	Δz_{t+1}	λ_{t+1}	r^f_{t+1}	ev_{t+1}
ev_t	0.22^{***}	0.03	0.01	-0.02^{***}	0.94^{***}
	(8.59)	(1.52)	(1.88)	(-5.76)	(39.11)
Obs.	273	273	273	273	273
Adj. R^2	0.38	0.01	0.04	0.23	0.88

Panel B: Cumulative Long-Run Predictive Regression

	$rx^{emp}_{t+1\to t+20}$	$\Delta e_{t+1\to t+20}$	$\lambda_{t+1\to t+20}$	$r^f_{t+1\to t+20}$
ev_t	1.17^{***}	-0.06	0.15	-0.09^{**}
	(5.72)	(-0.50)	(1.50)	(-2.07)
Obs.	253	253	253	253
Adj. R^2	0.57	0.01	0.08	0.15

Panel C: Direct Decomposition

Coefficients					Sum
$b^{(20)}_{rx}$	$b^{(20)}_{\Delta e}$	$b^{(20)}_{\lambda}$	$b^{(20)}_{rf}$	$b^{(20)}_{ev}$	$b^{(20)}_{r} - b^{(20)}_{\Delta e} - b^{(20)}_{\lambda} + b^{(20)}_{rf} + b^{(20)}_{ev}$
1.17	-0.06	0.15	-0.09	0.00	0.98

Notes: Table C.1 reports the direct decomposition results for the employee valuation ratio. Panel A documents next quarter predictive regressions on the *ev* ratio. Panel B documents the cumulative weighted long-run (20 quarters) predictive regressions on the *ev* ratio. Panel C reports results for the direct decomposition based on Equation (C.10). rx^{emp} is the excess employee return. Δe is the cash flow growth. λ is the retention rate. r^f is the risk-free rate. *ev* is the employee valuation ratio. The Newey-West adjusted *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

C.1.3 Return Predictability

In the previous section, we decomposed the employee valuation ratio and showed that it is primarily driven by variations in risk premia. Equation (C.7) suggests that stock and corporate bond market returns may incorporate this time-varying labor market risk premium information. In this section, we test whether the employee valuation ratio predicts future aggregate stock and corporate bond market returns. In order to facilitate interpretation, we standardize the employee valuation ratio to have a mean of zero and a standard deviation of one.

Table C.2: Forecasting Excess Stock Market Return

Panel A

			Coeff	t-stat	Adj. R^2			Coeff	t-stat	Adj. R^2
	t+1	CRSP	1.97***	4.24	0.05		CRSP	1.97***	4.60	0.05
	t+1	S&P 500	1.88***	4.18	0.05		S&P 500	1.89***	4.66	0.05
ev^1						ev^2				
	t+2	CRSP	1.48***	2.98	0.03		CRSP	1.65***	3.64	0.04
	t+2	S&P 500	1.42***	2.96	0.03		S&P 500	1.62***	3.82	0.04

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(14)	(15)	(16)
	rx_{t+1}	rx_{t+1}	rx_{t+1}	rx_{t+1}	rx_{t+1}	rx_{t+1}	rx_{t+1}	rx_{t+1}	rx_{t+1}	rx_{t+1}	rx_{t+1}	rx_{t+1}
ev_t	1.88***		1.67***		2.01***		1.98***		1.87***		1.80***	1.97***
	(4.18)		(3.20)		(4.63)		(4.39)		(3.61)		(4.11)	(3.71)
ik_t		-1.49***	-0.85									-0.36
		(-2.66)	(-1.49)									(-0.48)
dp_t				2.34**	2.85***							1.17
				(2.04)	(2.77)							(0.49)
ep_t						1.56	2.06*					1.88
						(1.08)	(1.67)					(0.74)
cay_t								81.28**	61.38			42.19
								(2.05)	(1.49)			(0.78)
$tbill_t$										-13.53*	-11.25*	-11.37*
										(-1.82)	(-1.65)	(-1.81)
Adj. R^2	0.05	0.03	0.06	0.01	0.08	0.00	0.06	0.02	0.06	0.01	0.06	0.08

Notes: Table C.2 reports OLS estimation results from regressions of one-period-ahead log excess stock returns on the ev^1 ratio and other predictors. Newey-West adjusted t-statistics are in parentheses. The ev^1 ratio is standardized to have mean zero and standard deviation of one. Data frequency is quarterly and returns are expressed in precentages. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Predicting Excess Stock Returns. The baseline forecasting regression is:

$$r_{t+1} - r^f_{t+1} = a + b_1 \times ev_t + \varepsilon_{t+1}, \tag{C.11}$$

where $r_{t+1} - r^f_{t+1}$ is the log stock market excess return, and ev is the employee valuation ratio. We report results using both the S&P 500 and the CRSP value-weighted stock returns.

Panel A of Table C.2 reports the baseline results predicting one-quarter- and two-quarter-ahead stock and excess stock returns based on ev^1 and ev^2. We find that ev^1 positively and significantly predicts next quarter excess stock returns. ev^1 alone explains 5 percent of variation in the next quarter return. For the excess return predictability tests, the coefficient estimate on ev^1 is 1.88. That is, a one-standard-deviation increase of ev^1 leads to a 1.88 percent increase in the next period excess stock returns. Similarly, ev^2 also positively and significantly predicts next quarter stock and excess stock returns. ev^2 alone explains 5 percent of variation in the next quarter return. Our estimates suggest that a one-standard-deviation increase in ev^2 leads to a 1.89 percent increase in

TABLE C.3: FORECASTING EXCESS CORPORATE BOND MARKET RETURN

	1	2	4	8	16	24		1	2	4	8	16	24
			Panel A							**Panel B**			
ev^1	0.95^{***}	1.61^{***}	2.05^{**}	0.73	-3.38	-0.41	ev^2	1.54^{***}	2.84^{***}	4.53^{***}	6.81^{**}	5.66^{*}	5.77^{*}
	(3.23)	(2.93)	(2.22)	(0.45)	(-1.65)	(-0.12)		(4.68)	(4.62)	(3.70)	(2.55)	(1.76)	(1.92)
Adj. R^2	0.05	0.07	0.05	-0.00	0.02	-0.01	Adj. R^2	0.13	0.21	0.24	0.23	0.07	0.06
ik	-0.85^{***}	-1.60^{***}	-2.29^{**}	-2.42	-0.42	0.54	ik	-0.85^{***}	-1.60^{***}	-2.29^{**}	-2.42	-0.42	0.54
	(-3.00)	(-2.90)	(-2.02)	(-1.09)	(-0.16)	(0.16)		(-3.00)	(-2.90)	(-2.02)	(-1.09)	(-0.16)	(0.16)
Adj. R^2	0.04	0.08	0.07	0.03	-0.01	-0.01	Adj. R^2	0.04	0.08	0.07	0.03	-0.01	-0.01
ev^1	0.75^{***}	1.20^{**}	1.41	-0.14	-3.90^{*}	-0.25	ev^2	1.50^{***}	2.75^{***}	4.62^{***}	7.87^{***}	9.02^{**}	11.08^{**}
	(2.81)	(2.37)	(1.61)	(-0.09)	(-1.89)	(-0.07)		(4.17)	(4.13)	(3.54)	(2.78)	(2.04)	(2.54)
ik	-0.61^{**}	-1.21^{**}	-1.85	-2.46	-1.47	0.47	ik	-0.06	-0.14	0.14	1.57	4.46	7.08^{*}
	(-2.38)	(-2.30)	(-1.60)	(-1.05)	(-0.57)	(0.14)		(-0.23)	(-0.29)	(0.15)	(1.07)	(1.58)	(1.85)
Adj. R^2	0.07	0.11	0.09	0.03	0.02	-0.01	Adj. R^2	0.12	0.20	0.23	0.23	0.10	0.13
ev^1	0.71^{**}	1.12^{*}	1.21	-0.83	$-5.46*$	-2.82	ev^2	1.66^{***}	3.04^{***}	4.97^{***}	7.81^{***}	7.54	8.78^{*}
	(2.31)	(1.95)	(1.18)	(-0.44)	(-1.89)	(-0.88)		(4.16)	(3.95)	(3.32)	(2.97)	(1.64)	(1.78)
ik	-0.61^{**}	-1.21^{**}	-1.89	-2.72	-2.07	-0.17	ik	0.06	0.08	0.42	1.62	3.56	5.95
	(-2.19)	(-2.11)	(-1.48)	(-1.10)	(-0.84)	(-0.06)		(0.20)	(0.13)	(0.35)	(0.91)	(1.11)	(1.37)
dp	-0.23	-0.46	-1.28	-4.73	-10.72	-13.35^{*}	dp	0.36	0.70	0.88	-0.53	-5.32	-8.05
	(-0.26)	(-0.28)	(-0.40)	(-0.91)	(-1.41)	(-1.79)		(0.48)	(0.49)	(0.32)	(-0.13)	(-0.84)	(-1.22)
cay	25.62	40.51	58.42	82.46	108.62	309.88	cay	31.18^{*}	50.16	71.45	76.99	47.81	286.86
	(1.33)	(1.12)	(0.92)	(1.00)	(0.85)	(1.51)		(1.77)	(1.54)	(1.22)	(0.91)	(0.40)	(1.60)
Adj. R^2	0.07	0.11	0.09	0.05	0.10	0.15	Adj. R^2	0.13	0.22	0.25	0.23	0.11	0.22

Notes: Table C.3 reports estimation results for regressions of the cumulative log excess corporate bond return (expressed in percentages) on the *ev* ratio. Newey-West corrected *t*-statistics are in parentheses. Data frequency is quarterly. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

the next period excess stock returns. Both ev^1 and ev^2 significantly predict 2-quarter ahead excess stock returns. Panel B of Table C.2 shows that the one-period-ahead return predictability results are robust to the inclusion of both the macroeconomic and market-based predictors such as the dividend-price ratio, earning-price ratio, consumption-wealth ratio, and relative bill rate.

Table C.15 explores the predictive power of the employee valuation ratio over long horizons. We consider predictive regressions of the form $\sum_{k=1}^{H} r_{t+k} - \sum_{k=1}^{H} r^f_{t+k} = a + b \times ev_t + \varepsilon_{t+H}$, where the dependent variable $\sum_{k=1}^{H} r_{t+k} - \sum_{k=1}^{H} r^f_{t+k}$ is the H-period ahead cumulative log excess stock market return. We find that the predictability increases as the horizon rises, and reaches its peak at around 16 quarters. The adjusted R^2 reach 13 percent for both ev^1 and ev^2 at the 4-quarter horizon. Interestingly, the employee valuation ratio subsumes the return predictive power of the aggregate capital investment rate.

Persistent Regressor. Stambaugh (1999) points out that persistent regressors may bias predictability tests. In order to address this potential issue, we estimate the size of the bias directly. Assume that *ev* follows an AR(1) process: $ev_{t+1} = \alpha + \rho ev_t + v_{t+1}$ with $|\rho| < 1$. Let the variance of v be denoted by σ_v^2, and the covariance between v and the error term in Equation (C.11) be denoted by $\sigma_{v\varepsilon}$. Stambaugh (1999) provides an estimate of the bias as $-\left(\sigma_{v\varepsilon}/\sigma_v^2\right)(1+3\rho)/T$, where T is the number of observations.

In our data, we estimate $\sigma_{v\varepsilon}/\sigma_v^2$ to be 0.011, and the sample size is 274. The bias term, $-\left(\sigma_{v\varepsilon}/\sigma_v^2\right)(1+3\rho)/274 = -0.011(1+3\rho)/274$, is small and negative relative to the point estimates from the return predictability regressions. Since the estimated coefficients from these regressions are positive, this small and negative bias cannot account for our results. If anything, it biases the results downward. Additionally, in untabulated results, we verify that our return predictability findings are robust to alternative standard error adjustments, such as the Hodrick (1992) correction.

Out-of-Sample Evidence. Welch and Goyal (2007) argue that the in-sample R^2 may not be a reliable benchmark for assessing the performance of predictive regressions. They examine the out-of-sample (R^2_{OOS}) values of many known predictors and find that most fail to outperform the historical average in out-of-sample tests.

We compute the out-of-sample R^2 values for the employee valuation ratio and summarize the results in Table C.5. The R^2_{OOS} values of ev are close to the in-sample R^2 values across various horizons. Specifically, the one-quarter-ahead R^2_{OOS} is 3 percent (2 percent) compared to the in-sample R^2 of 5 percent (5 percent) for ev^1 (ev^2). The four-quarter-ahead R^2_{OOS} is 9 percent (5 percent), compared to an in-sample R^2 of 13 percent (13 percent) for ev^1 (ev^2).

Predicting Excess Corporate Bond Returns. This section explored the performance of the employee valuation ratio in predicting excess corporate bond returns. The baseline regression is:

$$\sum_{k=1}^{H} r^b_{t+k} - \sum_{k=1}^{H} r^f_{t+k} = a + b \times ev_t + \varepsilon_{t+1},$$

where the dependent variable $\sum_{k=1}^{H} r^b_{t+k} - \sum_{k=1}^{H} r^f_{t+k}$ represents the H-period-ahead log excess corporate bond return.

Table C.3 reports the results. The ev ratio positively predicts excess corporate bond returns, consistent with the equity return predictability results. The coefficients on the ev^1 and ev^2 ratios are 0.95 and 1.54, respectively. That is, a one-standard-deviation increase in ev^1 and ev^2 is associated with a 0.95 percent and 1.54 percent increase in next-quarter excess bond returns, respectively.

The one-period-ahead adjusted R^2 values are 5 percent for ev^1 and 13 percent for ev^2.

Predictability is the strongest at the four-quarter horizon, where the adjusted R^2 reaches 5 percent for ev^1 and 24 percent for ev^2. However, the predictive power of the employee valuation ratio for corporate bond returns declines to zero at horizons beyond eight quarters. Consistent with the results for the aggregate stock market, the employee valuation ratio subsumes some of the predictive power of the investment rate in the bond market.

C.1.4 Employee Valuation Ratio Subsumes Aggregate Vacancy Posting Rate

In this section, we explore the return predictability of various components of the employee valuation ratio: the vacancy posting rate, the hiring rate, and the separation rate (Table C.6). We find that the vacancy posting rate significantly and negatively predicts next-period excess stock returns in the univariate regression. However, its predictive power is subsumed by the employee valuation ratio in the multivariate regression. The hiring rate and the separation rate do not predict future aggregate returns in univariate regressions. These results suggest that combining both the supply and demand sides of the labor market provides additional information on the aggregate risk premia in the equity market.

In sum, the aggregate time-series analysis reveals a robust empirical regularity in historical U.S. data. The employee valuation ratio—a measure constructed using labor market information that captures both labor demand and labor-market conditions—strongly predicts future excess stock and corporate bond returns. Its predictive power cannot be accounted for by a wide range of return predictors put forward by prior literature. The risk premium information embedded in the labor market provides important pricing information for the equity and corporate bond markets.

C.2 VAR Decomposition

Methodology. The point of departure is Equation (C.6). The VAR approach assumes that the economic system follows a VAR process of the following form:

$$X_{t+1} = \mu + AX_t + \varepsilon_{t+1}, \tag{C.12}$$

where X is a set of state variables. In this basic setup, we use a vector of state variables consisting of:

$$X = \left[rx^{emp} \;\; \Delta e \;\; \lambda \;\; r^f \;\; ev \right]', \tag{C.13}$$

where r^{emp}, Δe, λ, r^f are the return, rent growth, retention rate, and risk-free rate, respectively. ev is the log employee valuation ratio. Data frequency is quarterly.

With the VAR assumption, long-run conditional expectations can be expressed as:

$$\mathbb{E}_t \left(\sum_{i=1}^{\infty} \rho^s v_{t+i} \right) = G_v (I - \rho A)^{-1} X_t,$$

where $G_v = H_v A$ for $v \in \left\{ rx^{emp}, \Delta e, \lambda, r^f \right\}$ and $H_v = [0..1..0]$ is the selection matrix that picks the correct variable from the vector X.

Define the variance share of each of the three right-hand side components as follows:

$$varshare(v) = \frac{cov\left(ev_t, G_v (I - \rho A)^{-1} X_t\right)}{var(ev_t)}.$$

Applying variance operator on both sides of Equation (C.6), we obtain the following VAR-implied ev decomposition:

$$varshare\left(rx^{emp}\right) - varshare\left(\Delta e\right) - varshare(\lambda) + varshare\left(r^f\right) = 1. \tag{C.14}$$

In theory, Equation (C.14) has to hold due to its accounting nature. However, because of the VAR assumption and the finite sample constraint, the variance shares of the four components may not add up exactly to 1. Therefore, we can calculate the implied variance share of each variable based on the other three variables: $varshare(v) = 1 - \sum_{v' \neq v} varshare(v')$.

Campbell (1993) directly calculates the variance share of risk premium and backs out the implied variance share of the cash-flow growth. Later studies (e.g., Chen and Zhao, 2009) find that the results can be very different if the variance share of the cash-flow growth is calculated directly, instead of the risk premium. In order to mitigate this concern, we report the results for all three combinations and show that our decomposition results are robust.

Estimation by VAR. Panel A of Table C.7 reports OLS estimates of the A matrix (see Equation C.12). The standard errors are adjusted according to the Newey-West procedure.

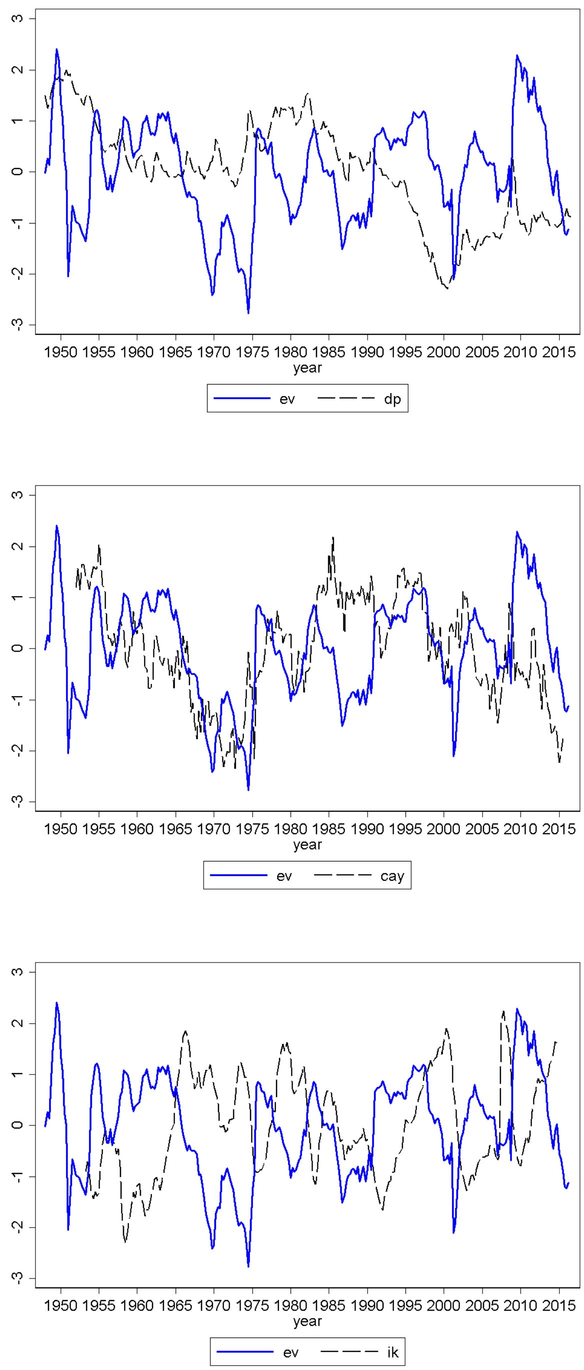
The employee valuation ratio significantly and positively predicts next period return. The variance decomposition results are reported in Panel B of Table C.7. The first three columns report the directly calculated variance shares of the three components. We find that the variation in expected excess return contributes to more than 100 percent of employee valuation movement. The variance share of the expected rent growth is negative at -11 percent.

We also calculate the implied variance shares of the three components using Equation (C.14). The last three columns of Table C.7 report our findings. The implied variance shares are close to the directly caclulated ones.

Discussion. How should we interpret the return decomposition results? Suppose we begin with a model that shuts down variation in the risk premium and retention rate; the baseline DMP model falls into this category. Models with matching efficiency variation but no variation in the risk premium or retention rate also fall into this group. If we perform the same return decomposition exercise in such models, we find that the expectation of cash flow growth fully accounts for the employee valuation ratio. This occurs because variation in the risk premium and retention rate is absent. What about models with endogenous separation? These models would predict that the combined variance shares of cash flow growth and retention rate sum to 100 percent—an implication that is rejected by the data. In sum, any model with a fixed risk premium fails to generate the patterns observed in the decomposition results.

C.3 Additional Graphs & Tables

FIGURE C.2: EMPLOYEE VALUATION RATIO AND OTHER EQUITY MARKET PREDICTORS



Notes: Figure C.2 plots the time-series of the employee valuation ratio alongside other equity market predictors, including the dividend-price ratio, the consumption-wealth ratio, and the capital investment rate. All series are standardized to have mean zero and standard deviation of one. Data spans the time period from 1948 to 2016.

TABLE C.4: SUMMARY STATISTICS FOR THE TIME-SERIES VARIABLES

Panel A: Basic Properties

	Mean	SD	Median	AC(1)	AC(4)	AC(8)
ev^1	0.00	1.00	0.07	0.93	0.62	0.27
ev^2	0.00	1.00	0.03	0.95	0.46	0.19
$r-r^f$	0.02	0.08	0.03	0.10	0.01	-0.02
ik (%)	10.59	1.03	10.44	0.95	0.64	0.27
dp	-3.48	0.43	-3.46	0.98	0.91	0.83
ep	-2.75	0.44	-2.82	0.96	0.74	0.58
cay	0.00	0.02	0.00	0.91	0.73	0.56
$tbill$	-0.00	0.07	0.00	0.67	0.12	-0.15

Panel B: Correlation Matrix

	ev^1	ev^2	$r-r^f$	ik (%)	dp	ep	cay	$tbill$
ev^1	1.00							
ev^2	0.83	1.00						
$r-r^f$	0.27	0.24	1.00					
ik (%)	-0.40	-0.66	-0.20	1.00				
dp	-0.18	-0.17	-0.04	-0.18	1.00			
ep	-0.20	-0.32	-0.02	0.05	0.74	1.00		
cay	0.28	0.26	-0.03	-0.26	0.17	0.09	1.00	
$tbill$	-0.09	-0.34	-0.15	0.16	0.02	0.20	-0.03	1.00

Notes: Table C.4 reports summary statistics for the aggregate time-series variables. Panel A reports the sample mean, median, standard deviation, and the first-, fourth-, and eighth-order autocorrelations. Panel B reports the correlation matrix. ev^1 and ev^2 are the employee valuation ratios (see text for details), both standardized to have mean zero and standard deviation of one.

TABLE C.5: OUT-OF-SAMPLE EXCESS STOCK RETURN PREDICTABILITY

(Quarters)	1	2	4	8	16	24
ev^1						
Adj. R^2	0.05	0.08	0.13	0.13	0.14	0.09
OOS R^2	0.03	0.05	0.09	0.09	0.10	0.07
ev^2						
Adj. R^2	0.05	0.09	0.13	0.11	0.14	0.15
OOS R^2	0.02	0.03	0.05	0.09	0.15	0.13

Notes: Table C.5 reports the in-sample (IS) and out-of-sample (OOS) R^2 values from univariate regressions of the *ev* ratio and other predictors across various forecast horizons. The OOS R^2 values are computed as follows. At each time t, we estimate the regression:

$$\sum_{i=1}^{K} rx_{t+i} = \alpha + \beta x_t + \varepsilon_{t+K}, \quad K \in \{1, 2, \ldots, 28\},$$

where x_t is the predictor (e.g., the *ev* ratio), and $\sum_{i=1}^{K} rx_{t+i}$ is the K-quarter-ahead cumulative excess stock return. Using this regression, we compute the fitted value $\hat{\mu}_{t+K}$ as the forecast of the K-quarter-ahead return. Each time the regression takes one additional observation, and produces a series of out-of-sample K-quarter ahead cumulative excess stock returns. Following Welch and Goyal (2007), the out-of-sample R^2 is defined as:

$$R^2_{\text{OOS}} = 1 - \frac{\sum_{j=S_0}^{T-K} \left(\sum_{i=1}^{K} rx_{j+i} - \hat{\mu}_{j+K}\right)^2}{\sum_{j=S_0}^{T-K} \left(\sum_{i=1}^{K} rx_{j+i} - \overline{\sum_{i=1}^{K} rx_{j+i}}\right)^2},$$

where $\overline{\sum_{i=1}^{K} rx_{j+i}}$ denotes the historical mean of the K-quarter-ahead cumulative excess return up to time j, and T is the sample size. The initial estimation window S_0 is set to 40 quarters (10 years).

TABLE C.6: EMPLOYMENT VALUATION RATIO AND COMPONENTS

(Percentage)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ev	1.88***		2.04**		2.22***		1.91***	2.03**
	(4.18)		(2.36)		(3.99)		(4.37)	(2.48)
Vacancy Posting Rate (%)		−2.79**	0.28					−0.72
		(-2.56)	(0.16)					(-0.41)
Hiring Rate (%)				0.27	0.85			0.95
				(0.24)	(0.86)			(0.85)
Separation Rate (%)						0.41	0.82	0.42
						(0.40)	(0.81)	(0.37)
Adj. R^2	0.05	0.02	0.05	-0.00	0.06	-0.00	0.05	0.05

Notes: Table C.6 reports estimation results for regressions of the log excess stock return on the *ev* ratio and its components. Newey-West adjusted t-statistics are in parentheses. Data frequency is quarterly. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.7: VAR DECOMPOSITION

Panel A: OLS Estimation

	rx^{emp}	Δe	λ	r^f	ev	Adj. R^2
rx^{emp}_{+1}	0.21**	-0.02	0.61	-1.34	0.16***	0.49
	(2.51)	(-0.35)	(1.76)	(-1.66)	(6.88)	
Δe_{+1}	-0.07	-0.04	-0.62	−2.23**	0.01	0.03
	(-0.90)	(-0.42)	(-1.40)	(-2.26)	(0.48)	
λ_{+1}	-0.01	0.01	0.82***	−0.34***	0.00	0.85
	(-0.83)	(1.15)	(20.07)	(-3.51)	(0.47)	
r^f_{+1}	0.01***	0.00	0.00	0.99***	0.00	0.94
	(4.49)	(-0.15)	(-0.29)	(40.35)	(-1.29)	
ev_{+1}	−0.33***	-0.01	-0.45	−2.58**	0.95***	0.89
	(-3.85)	(-0.17)	(-1.03)	(-2.03)	(34.25)	

Panel B: VAR Decomposition

Variance Share				Implied Variance Share			
rx^{emp}	Δe	λ	r^f	rx^{emp}	Δe	λ	r^f
1.29	-0.11	-0.15	-0.10	1.36	-0.04	-0.08	-0.03

Notes: Table C.7 reports the VAR decomposition results of the ev ratio in the time series. Panel A reports OLS estimates of the A matrix from Equation (C.12). Panel B shows the variance shares and implied variance shares attributed to each of the following components: excess employee return, cash-flow growth, retention rate, and the risk-free rate. rx^{emp} denotes the excess employee return, Δe is the cash-flow growth, λ is the retention rate, and ev is the employee valuation ratio. Newey-West adjusted t-statistics are in parentheses. Data frequency is quarterly. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.8: UNIT ROOT TESTS

	ADF t-statistic				Critical Values		
Lags	1	2	3	4	1%	5%	10%
ev^1	-3.385	-3.931	-4.314	-4.543	-3.458	-2.879	-2.570
ev^2	-4.196	-5.129	-5.137	-5.250	-3.458	-2.879	-2.570

Notes: Table C.8 reports results for the augmented Dickey–Fuller (ADF) test applied to the employee valuation ratio. The null hypothesis is the presence of a unit root. The column labeled "Lags" indicates the number of lagged first differences included in the test regression. Critical values at the 1%, 5%, and 10% significance levels are reported.

TABLE C.9: INDUSTRY-LEVEL PORTFOLIO RESULTS: OTHER VARIABLES

	Bottom	Middle	Top	Bottom - Top
Hiring Rate	1.08	0.96	0.88	0.20
	(3.03)	(2.95)	(2.03)	(0.74)
Separation Rate	1.26	0.90	1.08	0.18
	(3.91)	(2.67)	(2.49)	(0.59)
EE Rate	0.93	0.93	1.22	-0.29
	(2.50)	(2.74)	(3.63)	(-1.33)

Notes: Table C.9 reports the mean portfolio returns sorted by hiring rate, separation rate, or employer-to-employer (EE) transition rate at the industry level. Data covers sixteen 2-digit NAICS industries. In each quarter, the top portfolio consists of the two industries with the highest values of the sorting variable, while the bottom portfolio consists of the two industries with the lowest values. The remaining industries are grouped into a middle portfolio. Industry returns are value-weighted. Data spans the time period from the beginning of 2003 to the end of 2017.

TABLE C.10: PREDICTING DIVIDEND GROWTH

Dep. Var. *100	1	2	4	8	12	16	20
Dividend Growth							
ev	0.25	0.85*	2.14***	3.72***	3.67**	2.85	1.70
	(1.00)	(1.90)	(2.75)	(3.19)	(2.00)	(1.18)	(0.63)
Adj. R^2	0.01	0.06	0.12	0.12	0.08	0.04	0.01
Earnings Growth							
ev	2.84*	4.72**	6.98**	6.11*	2.89	-0.55	-2.76
	(1.94)	(2.25)	(2.53)	(1.84)	(0.81)	(-0.12)	(-0.50)
Adj. R^2	0.06	0.07	0.06	0.02	0.00	-0.00	-0.00

Notes: Table C.10 reports results for predictive regressions of dividend growth and earnings growth on the employee valuation ratio. Data frequency is quarterly. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.11: COMPONENTS OF CASH FLOW GROWTH

(Quarters)	1	2	4	8	12	16	20
Profit Growth							
ev	0.03	0.05	0.05	-0.01	-0.06	-0.08	-0.07
	(1.47)	(1.51)	(1.00)	(-0.17)	(-0.85)	(-1.09)	(-0.91)
Adj. R^2	0.01	0.02	0.01	0.00	0.01	0.02	0.01
Output Growth							
ev	0.01***	0.02***	0.03***	0.02	0.02	0.02	0.03
	(4.62)	(4.16)	(3.31)	(1.88)	(1.36)	(1.27)	(1.49)
Adj. R^2	0.07	0.10	0.11	0.07	0.05	0.05	0.07
Compensation Growth							
ev	0.01***	0.01***	0.02***	0.02	0.02	0.02	0.02
	(2.69)	(2.72)	(2.47)	(1.82)	(1.50)	(1.53)	(1.74)
Adj. R^2	0.03	0.05	0.07	0.06	0.05	0.06	0.07
Non-Labor Cost Growth							
ev	0.02***	0.03***	0.04***	0.04	0.05	0.05	0.05
	(2.61)	(2.51)	(2.08)	(1.50)	(1.58)	(1.61)	(1.63)
Adj. R^2	0.02	0.05	0.06	0.06	0.07	0.08	0.09

Notes: Table C.11 reports results for predictive regressions of each component of the profit growth on the employee valuation ratio. The set of components include output growth, compensation growth, and non-labor cost growth. Data frequency is quarterly. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.12: VAR DECOMPOSITION WITH EE TRANSITION RATE

Panel A: OLS Estimation

	rx^{emp}	Δe	λ	r^f	ev	Adj. R^2
rx^{emp}_{+1}	-0.05	-0.12^{**}	1.51	0.83	0.14^{***}	0.35
	(-0.40)	(-2.16)	(1.42)	(0.50)	(6.34)	
Δe_{+1}	-0.28	-0.20	-0.48	-2.38	0.05	0.08
	(-1.94)	(-1.40)	(-0.59)	(-1.22)	(1.21)	
λ_{+1}	-0.02^{***}	-0.00	0.63^{***}	-0.49^{**}	0.00	0.76
	(-2.84)	(-0.82)	(6.37)	(-2.49)	(1.80)	
r^f_{+1}	0.01^{***}	-0.00^{**}	-0.07^{***}	0.93^{***}	0.00	0.97
	(3.33)	(-2.31)	(-2.80)	(22.01)	(1.65)	
ev_{+1}	-0.26	-0.08	-1.34	-4.95	0.95^{***}	0.89
	(-1.22)	(-0.52)	(-1.05)	(-1.82)	(18.02)	

Panel B: VAR Decomposition

Variance Share				Implied Variance Share			
rx^{emp}	Δe	λ	r^f	rx^{emp}	Δe	λ	r^f
1.19	-0.04	-0.12	-0.03	1.19	-0.04	-0.12	-0.03

Notes: Table C.12 reports VAR decomposition results for the ev ratio in the time series. Panel A reports OLS estimates of matrix A from Equation (C.12). Panel B reports the variance shares and implied variance shares attributable to excess employee return, cash-flow growth, retention rate, and the risk-free rate. rx^{emp} denotes excess employee returns, Δe is cash-flow growth, and λ is the retention rate, calculated as one minus the employer-to-employer (EE) transition rate from Fallick and Fleischman (2004). ev is the employee valuation ratio. Newey-West adjusted t-statistics are reported in parentheses. Data frequency is quarterly; the sample time period is from 1994 to 2016. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.13: MANAGER INFORMATION

	ev_t (1)	ev_t (2)	ev_t (3)	ev_t (4)	ev_t (5)
$Confidence_t$	-0.01^{***}	-0.02^{***}	-0.01^{***}	-0.01^{***}	-0.01^{*}
	(-3.59)	(-2.40)	(-3.14)	(-3.13)	(-1.77)
dp_t		-0.31			-0.18
		(-0.87)			(-0.58)
ep_t			-0.06		-0.07
			(-1.02)		(-0.80)
cay_t				2.68	1.96
				(1.86)	(1.23)
Obs	57	57	57	54	54
Adj. R^2	0.16	0.17	0.17	0.26	0.26

Notes: Table C.13 reports estimation results for regressions of the employee valuation ratio on firm manager confidence index from the Duke CFO Outlook Survey. Data frequency is quarterly. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.14: EMPLOYMENT VALUATION RATIO AND COMPONENTS: ADDITIONAL TESTS

(Percentage)	(1)	(2)	(3)	(4)
ev		2.02^{***}		2.97^{***}
		(3.41)		(3.22)
Initial Claim Rate (%)	3.48^{*}	3.46^{*}		
	(1.77)	(1.81)		
EE Rate (%)			-0.61	0.11
			(-0.25)	(0.46)
Adj. R^2	0.01	0.06	-0.01	0.09

Notes: Table C.14 reports estimation results for regressions of log excess stock returns on the *ev* ratio and its components. Newey-West corrected t-statistics are in parentheses. Data frequency is quarterly. Initial claim rate data starts from 1967 and employer-to-employer rate data starts from 1994. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.15: FORECASTING LONG HORIZON EXCESS STOCK MARKET RETURN

	1	2	4	8	16	24		1	2	4	8	16	24
			Panel A							**Panel B**			
ev^1	**1.88*****	**3.35*****	**6.14*****	**8.54*****	**11.69*****	12.34**	ev^2	1.89***	3.54***	6.16***	7.93***	11.57***	15.03***
	(4.18)	(4.13)	(4.01)	(3.45)	(3.38)	(2.52)		(4.66)	(4.77)	(4.43)	(3.72)	(3.28)	(3.10)
Adj. R^2	0.05	0.08	0.13	0.13	0.14	0.09	Adj. R^2	0.05	0.09	0.13	0.11	0.14	0.15
ik	-1.49***	-2.81***	-4.64**	-5.83**	-11.86***	-12.99**	ik	-1.49***	-2.81***	-4.64**	-5.83**	-11.86***	-12.99**
	(-2.66)	(-2.60)	(-2.50)	(-2.19)	(-3.66)	(-2.30)		(-2.66)	(-2.60)	(-2.50)	(-2.19)	(-3.66)	(-2.30)
Adj. R^2	0.03	0.05	0.08	0.06	0.17	0.15	Adj. R^2	0.03	0.05	0.08	0.06	0.17	0.15
ev^1	1.67***	2.78***	5.09***	7.38**	9.99**	6.03	ev^2	1.77**	2.96**	5.26**	7.58**	10.99**	12.48*
	(3.20)	(2.89)	(2.84)	(2.52)	(2.58)	(1.10)		(2.32)	(2.08)	(2.23)	(2.09)	(2.18)	(1.66)
ik	-0.85	-1.75	-2.69	-2.94	-7.66*	-10.38	ik	-0.39	-0.97	-1.38	-1.01	-4.52	-4.71
	(-1.49)	(-1.54)	(-1.40)	(-0.97)	(-1.79)	(-1.59)		(-0.44)	(-0.57)	(-0.49)	(-0.23)	(-0.78)	(-0.55)
Adj. R^2	0.06	0.09	0.15	0.14	0.26	0.17	Adj. R^2	0.05	0.08	0.12	0.12	0.24	0.21
ev^1	1.84***	3.09***	5.58***	7.46**	9.05*	3.95	ev^2	2.27**	3.96***	7.11***	10.00***	12.91**	16.13***
	(3.48)	(3.44)	(3.30)	(2.33)	(1.81)	(0.68)		(2.51)	(2.65)	(3.21)	(3.28)	(2.56)	(2.63)
ik	-0.47	-0.90	-0.90	0.12	-4.42	-6.56	ik	0.29	0.47	1.56	3.83	0.62	2.45
	(-0.77)	(-0.79)	(-0.50)	(0.05)	(-1.43)	(-1.43)		(0.27)	(0.25)	(0.55)	(1.15)	(0.17)	(0.46)
dp	2.43*	5.12**	10.23**	16.12**	20.35***	29.50***	dp	2.89*	6.00**	11.80**	18.47**	23.58***	37.50***
	(1.82)	(2.14)	(2.49)	(2.25)	(2.82)	(5.60)		(1.77)	(2.16)	(2.59)	(2.48)	(3.61)	(8.45)
cay	31.27	75.82	186.43**	436.61***	654.66***	804.65***	cay	36.36	83.36*	200.21**	446.32***	658.97***	710.08***
	(1.14)	(1.53)	(2.29)	(3.83)	(4.43)	(4.82)		(1.37)	(1.71)	(2.49)	(3.87)	(4.51)	(5.40)
Adj. R^2	0.08	0.13	0.25	0.36	0.53	0.50	Adj. R^2	0.08	0.14	0.25	0.37	0.54	0.58

Notes: Table C.15 reports estimation results for the long-term regressions of cumulative log excess stock returns (in percent) on the *ev* ratio. Newey-West adjusted t-statistics are in parentheses. Both ev^1 and ev^2 are standardized to have mean zero and standard deviation of one. Data frequency is quarterly. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Appendix D: Model Appendix

The computation of the model can be broadly divided into three parts: (1) simplification of programming problems by way of combining household's and firms' optimization problems, (2) computation of the model at the steady-state, and (3) solving for the equilibrium of the model with aggregate fluctuations using perturbation techniques. In what follows, we lay out the key details of the numerical algorithm. We start with a formal definition of the recursive competitive equilibrium for the model outlined in Section 5.

D.1 Definition of Equilibrium

The recursive competitive equilibrium for this economy consists of the following functions:

$$\left\{v, v^F, v^U, vc, n', C, M\right\},$$

such that:

1. (C) solves the household's problem,
2. v, v^F, v^U solve the firm's problem (9)-(11), and (vc, n') are the corresponding policy functions,
3. stochastic discount factor M satisfies (16),
4. goods market clears

$$C(\mathbf{S}) = Y(\mathbf{S}) - AC(\mathbf{S}) - \kappa VC(\mathbf{S}),$$

where

$$\begin{aligned}
Y(\mathbf{S}) &= \int e^Z e^z n^\nu \mathrm{d}\mu, \\
AC(\mathbf{S}) &= \int AC(n, vc)\mathrm{d}\mu \\
VC(\mathbf{S}) &= \int vc(n, z; \mathbf{S})\mathrm{d}\mu,
\end{aligned}$$

5. law of motion for the aggregate state vector $\Gamma(\cdot)$ and the cross-sectional distribution of firms μ is consistent with firms' policy functions.

D.2 Analysis of the Model

The model outlined in Section 5 incorporates optimization problems for a representative household and heterogeneous firms. This implies that, first, we need to solve two programming problems, and then make sure that the agents' decisions are consistent with each other and that markets clear. Fortunately, it is possible to combine the optimality conditions for the household's and firms' Bellman equations, and thereby reduce the computational complexity of the problem at hand. Using $C(\mathbf{S})$ to denote the market clearing value of household consumption, one can show that market-clearing requires firms' state-contingent discount factor to be consistent with the household marginal rate of substitution over time:

$$M(\mathbf{S},\mathbf{S}') = \beta \frac{U_C'(C(\mathbf{S}')S')}{U_C'(C(\mathbf{S})S)}.$$

Following Khan and Thomas (2008), we compute for the recursive competitive equilibrium effectively substituting the equilibrium implications of household optimization into the recursive problems faced by the firms. This means that we scale all value functions by $p(\mathbf{S})$—the marginal utility of the household with respect to equilibrium consumption $C(\mathbf{S})$.

D.3 Steady-State

We use collocation methods to solve the firm's functional equations. In practice, we use Chebyshev polynomials to approximate value functions.

We set up a grid of collocation nodes $\mathscr{N} \times \mathscr{Z}$, with N_i nodes in each dimension, $i \in \{\mathscr{N}, \mathscr{Z}\}$. The computation of the stationary state of the model proceeds in the following 4 steps:

1. guess the equilibrium vacancy-unemployment ratio θ,
2. solve for individual decision rules n' and vc,
3. given the decision rules, compute the stationary distribution of firms over the idiosyncratic state space,

4. compute the implied vacancy-unemployment ratio. If the implied θ deviates from the guessed value by more than a prespecified tolerance, update the guess for θ accordingly and return to Step 2. Otherwise, terminate.

D.3.1 Approximation of Value Functions

We directly approximate (normalized by the household's marginal utility) ex-ante value function $V(\cdot)$. We represent this value function as a weighted sum of orthogonal polynomials:

$$V(n,z) = \sum_{a,b=1,1}^{N_{\mathscr{N}} N_{\mathscr{Z}}} \theta^{ab} T^{a}(n) T^{b}(z),$$

where $\{\theta^{a,b}\}$ are approximation coefficients, and $T^{i}(\cdot)$ is the Chebyshev polynomial of order i.

We use a collocation method to solve for $\{\theta^{a,b}\}$. Collocation method requires setting the residual equation to hold exactly at $N = N_{\mathscr{N}} \times N_{\mathscr{Z}}$ points; therefore, we essentially solve for N unknown coefficients. We compute the basis matrices for Chebyshev polynomials using Miranda and Fackler (2004) Compecon toolbox. Subsequently, we solve for a vector of unknown coefficients using Newton's method. A much slower alternative is to iterate on the value function. Given the current guess of coefficients, we solve for the optimal policy $n'(n,z)$ using vectorized golden search. After we solve for the policy function, we recompute decision rules on a finer grid, and, subsequently, compute the stationary distribution.

D.3.2 Stationary Distribution

When we solve for a stationary distribution, we iterate on a mapping using firms' decisions rules:

$$L' = \mathbf{Q}' L,$$

where L is a current distribution of firms across the state space. Matrix $\mathbf{Q}$ is a transition matrix, which determines how mass of firms shifts in the (n,z)-space. It is a direct product of three transition matrices $\mathbf{Q}_n$, and $\mathbf{Q}_z$:

$$\mathbf{Q} = \mathbf{Q}_n \odot \mathbf{Q}_z,$$

which govern the shift of mass along n- and z-dimensions, respectively. While $\mathbf{Q}_z$ is completely determined by the exogenous stochastic process, matrix $\mathbf{Q}_n$ is constructed so that the model generates an unbiased distribution in terms of aggregates.[14] More precisely, element (i,j) of the transition matrix $\mathbf{Q}_n$ informs which fraction of firms with the current idiosyncratic state n_i will end up having n_j tomorrow. Therefore, this entry of the matrix is computed as:

$$\mathbf{Q}_n(i,j) = \left[\mathbf{1}_{n' \in [n_{j-1}, n_j]} \frac{n' - n_j}{n_j - n_{j-1}} + \mathbf{1}_{n' \in [n_j, n_{j+1}]} \frac{n_{j+1} - n'}{n_{j+1} - n_j}\right].$$

Tensor product of matrices $\mathbf{Q}_n$ and $\mathbf{Q}_z$ is computed using the `dprod` function from the Miranda and Fackler (2004) toolkit.

D.4 Model with Aggregate Shocks

We solve the model with aggregate uncertainty using a second-order perturbation around the non-stochastic steady-state in `Dynare`. This level of approximation is sufficient to capture the average risk-free rate and equity premium, as well as their (unconditional) volatilities.

Since we are interested in solving the model using high-order perturbation techniques, it becomes computationally prohibitive to approximate the distribution even with a coarse histogram. Instead, we follow Winberry (2018), who builds on Algan, Allais and Den Haan (2008), and approximate the density of firms over the idiosyncratic state space using a log-normal parametric family. In what follows, we outline the main steps of this procedure.

Specifically, we approximate the density $g(n,z)$ using the following functional form:

$$g(n,z) \approx g_0 \exp\left\{ g_1^1(z - m_1^1) + g_1^2(\log n - m_1^2) + \sum_{i=2}^{n_g} \sum_{j=0}^{i} g_i^j \left[(z - m_1^1)^{i-j} (\log n - m_1^2)^j - m_i^j \right] \right\}, \tag{D.1}$$

where n_g indexes the degree of approximation. The parameters g_0, g_1^1, g_1^2, and g_i^j (for $i,j = 0,\ldots,n_g$) define the shape of the distribution, and m_1^1, m_1^2, and m_i^j are centralized moments.

The parameter vector $\mathbf{g} = (g_0, \ldots, g_{n_g}^{n_g})$ and moment vector $\mathbf{m} = (m_1^1, \ldots, m_{n_g}^{n_g})$ must be internally

[14] See Young (2010) for more details.

consistent in the sense that the moments are implied by the parameters:

$$
\begin{aligned}
m_1^1 &= \iint z\, g(n,z)\, \mathrm{d}z\, \mathrm{d}n, \\
m_1^2 &= \iint \log n\, g(n,z)\, \mathrm{d}z\, \mathrm{d}n, \\
m_i^j &= \iint (z - m_1^1)^{i-j} (\log n - m_1^2)^j\, g(n,z)\, \mathrm{d}z\, \mathrm{d}n \quad \text{for } i = 2, \ldots, n_g,\ j = 0, \ldots, i.
\end{aligned}
\tag{D.2}
$$

Given a vector of parameters $\mathbf{g}$, Algan, Allais and Den Haan (2008) provide a simple and robust method for solving the system (D.2) for the density parameters $\mathbf{g}$. Thus, the vector of moments $\mathbf{m}$ fully characterizes the approximated density. Therefore, we approximate the infinite-dimensional aggregate state $\mathbf{S} = (Z, \mu)$ with the finite-dimensional representation $(Z, \mathbf{m})$.

The fact that the distribution is completely characterized by its moments $\mathbf{m}$ suggests a convenient method for approximating the law of motion for the cross-sectional distribution:

$$
\begin{aligned}
m_1^1 &= \iiint (\rho_z z + \omega_z')\, p(\omega_z')\, g(n,z;\mathbf{m})\, d\omega_z'\, dz\, dn, \\
m_1^2 &= \iiint \left[p^F \log n^F(n,z;Z,\mathbf{m}) + \left(1 - p^F\right) \log n^U(n,z;Z,\mathbf{m})\right] \\
&\quad \times p(\omega_z')\, g(n,z;\mathbf{m})\, d\omega_z'\, dz\, dn, \\
m_i^j(Z,\mathbf{m}) &= \iiint (\rho_z z + \omega_z' - m_1^1)^{i-j} \left\{p^F (\log n^F(n,z;Z,\mathbf{m}) - m_1^2)^j \right. \\
&\quad \left. + \left(1 - p^F\right) (\log n^U(n,z;Z,\mathbf{m}) - m_1^2)^j \right\} \\
&\quad \times p(\omega_z')\, g(n,z;\mathbf{m})\, d\omega_z'\, dz\, dn,
\end{aligned}
\tag{D.3}
$$

where $p(\cdot)$ is the p.d.f. of idiosyncratic productivity shocks, and n^F and n^U denote labor choices for firms operating under favorable and unfavorable labor market conditions, respectively.

The system (D.3) provides a mapping from the current aggregate state into next period's moments $\mathbf{m}'(Z,\mathbf{m})$ by integrating decision rules against the implied density. We solve for the steady-state values of the moments $\mathbf{m}^*$ by iterating on this mapping.