

A Labor Capital Asset Pricing Model

LARS-ALEXANDER KUEHN, MIKHAIL SIMUTIN, and JESSIE JIAXU WANG*

ABSTRACT

We show that labor search frictions are an important determinant of the cross-section of equity returns. Empirically, we find that firms with low loadings on labor market tightness outperform firms with high loadings by 6% annually. We propose a partial equilibrium labor market model in which heterogeneous firms make dynamic employment decisions under labor search frictions. In the model, loadings on labor market tightness proxy for priced time-variation in the efficiency of the aggregate matching technology. Firms with low loadings are more exposed to adverse matching efficiency shocks and require higher expected stock returns.

DYNAMICS IN THE LABOR MARKET are an integral component of business cycles. More than 10% of U.S. workers separate from their employers each quarter. Some move directly to a new job with a different employer, some become unemployed, and some exit the labor force. These large flows are costly for firms, because they need to spend resources to search for and train new employees.¹

Building on the seminal contributions of Diamond (1982), Mortensen (1982), and Pissarides (1985), we show that labor search frictions are an important

*Lars-Alexander Kuehn is at the Tepper School of Business, Carnegie Mellon University; Mikhail Simutin is at the Rotman School of Management, University of Toronto; Jessie Jiaxu Wang is at the W. P. Carey School of Business, Arizona State University. We thank the Editor Ken Singleton, two anonymous referees, Frederico Belo, Ilan Cooper, Andres Donangelo, Vito Gala, Brent Glover, Bart Hobijn, Burton Hollifield, Finn Kydland, Christian Lundblad, Stefan Nagel, Stavros Panageas, Dimitris Papanikolaou, Nicolas Petrosky-Nadeau, Chris Telmer, Lu Zhang, conference participants of the 2012 Western Economic Association Annual Conference, 2012 Midwest Macroeconomics Meeting, 2013 Midwest Finance Association Meeting, 2013 ASU Sonoran Winter Finance Conference, 2013 SFS Finance Cavalcade, 2013 CAPR Workshop on Production Based Asset Pricing at BI Norway, 2014 American Finance Association Meeting, 2016 CSEF-EIEF-SITE Conference on Finance and Labor, and seminar participants at Carnegie Mellon University, Goethe Universität Frankfurt, ESMT, Humboldt Universität Berlin, University of Virginia (Darden), University of Michigan, Tsinghua University, University of Washington, Georgetown University, Vienna University of Economics and Business, University of Oklahoma, and University of Texas at Dallas for helpful comments. Mikhail Simutin gratefully acknowledges support from the Social Sciences and Humanities Research Council (Grant 430-2013-0588). The authors have no conflicts of interest, as identified in the *Journal of Finance*'s disclosure policy.

¹ According to the U.S. Department of Labor, the cost of replacing a worker amounts to one-third of a new hire's annual salary. Direct costs include advertising, sign-on bonuses, headhunter fees, and overtime. Indirect costs include recruitment, selection, training, and decreased productivity while current employees pick up the slack. Similar evidence is presented in Blatter, Muehleman, and Schenker (2012). Davis, Faberman, and Haltiwanger (2006) provide a review of aggregate labor market statistics.

DOI: 10.1111/jofi.12504

determinant of the cross-section of equity returns. In search models, firms post vacancies to attract workers, and unemployed workers look for jobs. The likelihood of matching a worker with a vacant job is determined endogenously and depends on the congestion of the labor market, which is measured as the ratio of vacant positions to unemployed workers. This ratio, termed *labor market tightness*, is the key variable of our analysis. Intuitively, a high ratio implies that filling a vacancy is difficult because firms' hiring activity is strong and the pool of unemployed workers is shallow.

We begin by studying the empirical relation between labor market conditions and the cross-section of equity returns. We measure aggregate labor market tightness as the ratio of the monthly vacancy index published by the Conference Board to the unemployed population (see, for example, Shimer (2005)). To measure the sensitivity of firm value to labor market conditions, we estimate loadings of equity returns on the log changes in labor market tightness controlling for the market return. We use rolling firm-level regressions based on three years of monthly data to allow for time-variation in the loadings. Using the panel of U.S. stock returns from 1951 to 2014, we show that loadings on the changes in labor market tightness robustly and negatively predict future stock returns in the cross-section. **Sorting stocks into deciles on the estimated loadings, we find an average spread in future returns of firms in the low- and high-loading portfolios of 6% per year.** We emphasize that this return differential is not due to mispricing. While it cannot be attributed to differences in loadings on common risk factors, such as those of the CAPM or the Fama-French (1993) three-factor model, it arises rationally in our model due to risk associated with labor market frictions as we describe in detail below.

To ensure that the relation between labor search frictions and future stock returns is not driven by firm characteristics known to relate to future returns, we run Fama-MacBeth (1973) regressions of stock returns on lagged estimated loadings and other firm-level attributes. We include conventionally used control variables such as a firm's market capitalization and book-to-market ratio as well as recently documented determinants of the cross-section of stock returns that may potentially correlate with labor market tightness loadings, such as asset growth (Cooper, Gulen, and Schill (2008)) and hiring rates (Belo, Lin, and Bazdresch (2014)). The Fama-MacBeth (1973) analysis confirms the robustness of results obtained in portfolio sorts. In particular, the coefficients on labor market tightness loadings are negative and statistically significant in all regression specifications. Moreover, the magnitude of the coefficients suggests that the relation is economically important: for a one-standard-deviation increase in loadings, future annual returns decline by approximately 1.5%.

Our main results hold not only when controlling for firm-level characteristics as in Fama-MacBeth (1973) regressions but also after accounting for macro variables. For example, labor market tightness and industrial production are correlated and highly procyclical. However, we show that loadings on labor market tightness contain information about future returns, while loadings on industrial production do not. We also find that, unlike many cross-sectional predictors of equity returns that are priced mainly within industries, labor

market tightness loadings contain information about future returns when considered both within and across industries. Numerous robustness tests confirm our results. For example, excluding micro stocks has little effect on the return spread across labor market tightness portfolios.

To interpret the empirical findings, we propose a labor-market-augmented capital asset pricing model. Building on the search and matching framework pioneered by Diamond-Mortensen-Pissarides, we develop a partial equilibrium labor search model and study its implications for firm employment policies and stock returns. For tractability, we do not model the supply of labor as an optimal household decision; instead we assume an exogenous pricing kernel. Our model features a cross-section of firms with heterogeneity in their idiosyncratic profitability shocks and employment levels. Given the pricing kernel, firms maximize their value by posting vacancies to recruit workers or by firing workers to downsize. Both firm policies are costly at proportional rates.

In the model, the fraction of successfully filled vacancies depends on labor market conditions as measured by labor market tightness (the ratio of vacant positions to unemployed workers). As more firms post vacancies, the likelihood that vacant positions are filled declines, thereby increasing the costs to hire new workers. Since labor market tightness is a function of all firms' vacancy policies, it has to be consistent with individual firm's policies and is thus determined as an equilibrium outcome. In equilibrium, the matching of unemployed workers and firms is imperfect, which results in both equilibrium unemployment and rents. These rents are shared between each firm and its workforce according to a Nash bargaining wage rate.

Our model is driven by two aggregate shocks, both of which are priced: a productivity shock and a shock to the efficiency of the matching technology, which was first studied by Andolfatto (1996). The literature has shown that variation in matching efficiency can arise for many reasons, and we are agnostic about the exact source. For example, Pissarides (2011) emphasizes that matching efficiency captures the mismatch between the skill requirements of jobs and the skill mix of the unemployed, the differences in geographical location between jobs and unemployed, and the institutional structure of an economy with regard to the transmission of information about jobs.

Aggregate productivity and matching efficiency are not directly observable in the data. To quantitatively compare the model with the data, we map the aggregate productivity and matching efficiency shocks onto the market return and labor market tightness, which are observable. As a result, we show that expected excess returns obey a two-factor structure in the market return and labor market tightness. We call the resulting model the *Labor Capital Asset Pricing Model*. Importantly, a one-factor CAPM does not span all risks and thus implies mispricing, in line with the data.

Our model replicates the negative relation between loadings on labor market tightness and expected returns. Intuitively, firm policies are driven by opposing cash flow and discount rate effects. On the one hand, positive shocks to matching efficiency decrease marginal hiring costs. This cash flow channel implies an increase in optimal vacancy postings. On the other hand, positive

shocks to matching efficiency are associated with an increase in discount rates. This assumption is consistent with the general equilibrium view that positive efficiency shocks lead to lower consumption as firms spend more resources in hiring. This discount rate channel implies a reduction in the present value of job creation, and hence a decrease in optimal vacancy postings. As an equilibrium outcome of the labor market, the cash flow channel dominates the discount rate effect at the aggregate level. Thus, labor market tightness is positively related to matching efficiency shocks, so that loadings on labor market tightness are positively related to return sensitivities to matching efficiency shocks.

The cross-sectional differences in returns arise from frictions and heterogeneity in idiosyncratic productivity. Due to proportional hiring and firing costs, optimal firm policies exhibit regions of inactivity, in which firms neither hire nor fire workers. Some firms are hit by low idiosyncratic productivity shocks, so that hiring is not optimal when matching efficiency is high. For these firms, the discount rate channel dominates the cash flow channel, thereby depressing valuations. Their dividends are reduced not only by low idiosyncratic productivity shocks but also by higher wages, which arise from tighter labor markets, and by firing costs. Consequently, these firms have countercyclical dividends and valuations with respect to matching efficiency shocks, which renders them more risky. Since labor market tightness loadings and loadings on matching efficiency are positively related, our model can replicate the negative relation between labor market tightness loadings and expected returns.

We strengthen the link between the model's predictions and the data by examining the relation between labor market tightness loadings and the cyclicalities of firms' labor decisions. In our model, firms that are hit by adverse idiosyncratic productivity shocks may optimally decide not to hire even when the marginal cost of hiring is low. These firms are risky as they have countercyclical hiring policies and dividends with respect to matching efficiency shocks, and so have low labor market tightness loadings. When matching efficiency is high, we would thus expect these firms to have lower vacancy rates, hiring rates, employee growth rates, wages, and productivity, and higher firing rates, than firms with high loadings. The opposite should hold when matching efficiency is low. Importantly, these theoretical predictions concern the *cyclicity* of labor characteristics, and are both distinct from and complimentary to the predictions about the *level* of labor characteristics studied in prior literature (e.g., Belo, Lin, and Bazdresch (2014)).

We confirm our theoretical predictions in simulations and also provide supporting empirical evidence. Our empirical analyses are based on granular data from several sources, including Job Openings and Labor Turnover Survey, Quarterly Census of Employment and Wages, and Quarterly Workforce Indicators. Using these data, we compute time-series correlations between aggregate labor market tightness and labor characteristics for portfolios sorted by labor market tightness loadings. Consistent with our theory, we find that the correlations increase with the loadings for vacancy rates, hiring rates, employee growth rates, wages, and profitability, and decrease for firing rates and labor share. By contrast, we find that the average levels of these labor

characteristics do not display a significant pattern across portfolios. This set of findings confirms the economic mechanism of our model and distinguishes our results from prior work.

This paper contributes to the macroeconomic literature by building on the canonical search and matching model of Mortensen and Pissarides (1994). The importance of labor market dynamics for the business cycle has long been recognized; see, for example, Merz (1995) and Andolfatto (1996). While the standard model assumes a representative firm, firm heterogeneity has been considered by Cooper, Haltiwanger, and Willis (2007), Mortensen (2010), Elsby and Michaels (2013), and Fujita and Nakajima (2016). These papers have similar model features to ours but do not study asset prices.

Our paper also adds to the production-based asset pricing literature pioneered by Cochrane (1991) and Jermann (1998). Starting with Berk, Green, and Naik (1999), a large literature studies cross-sectional asset pricing implications of firm-level real investment decisions (e.g., Gomes, Kogan, and Zhang (2003), Carlson, Fisher, and Giammarino (2004), Zhang (2005), and Cooper (2006)). More closely related are Papanikolaou (2011) and Kogan and Papanikolaou (2013, 2014), who show that investment-specific shocks are related to firm-level risk premia. We differ by studying frictions in the labor market, in particular, shocks to the efficiency of the matching technology.

The impact of labor market frictions on the aggregate stock market has been analyzed by Danthine and Donaldson (2002), Merz and Yashiv (2007), Lochstoer and Bhamra (2009), and Kuehn, Petrosky-Nadeau, and Zhang (2012).² A related line of literature links cross-sectional asset prices to labor-related firm characteristics: Gourio (2007), Chen, Kacperczyk, and Ortiz-Molina (2011), and Favilukis and Lin (2016) consider labor operating leverage arising from rigid wages; Donangelo (2014) focuses on labor mobility; Donangelo (2017) studies how firm-level labor share affects the value premium; Eisefeldt and Papanikolaou (2013) study organizational capital embedded in specialized labor input; and Belo et al. (2016) focus on labor force heterogeneity in worker skills. We differ by exploring the impact of search costs on cross-sectional asset prices.

Closest to our paper is Belo, Lin, and Bazdresch (2014), who also emphasize that firms' hiring policies affect cross-sectional risk premia. They find that firm hiring rates predict returns in the data and explain this finding with a neo-classical Q -theory model with labor and capital adjustment costs. In contrast, we base our analysis on conditional risk loadings and emphasize the risk implications arising in a partial equilibrium labor search model. Search frictions prevent certain firms from flexibly expanding when the labor market matching is more efficient. The cyclicity of firm hiring policies with respect to labor market tightness captures their risk exposure to matching efficiency shocks, which is priced in the cross-section.

² Whereas we consider labor market frictions, Jagannathan and Wang (1996), Berk and Walden (2013), and Eiling (2013) study human capital risk.

The remainder of the paper is organized as follows. In Section I, we test whether loadings on labor market tightness predict future returns in the cross-section. In Section II, we derive a partial equilibrium labor market model and study its implications for expected returns in Section III. In Section IV, we inspect the model mechanism using micro-level data. Section V concludes. Details on data construction, proofs, and computational methods are delegated to the Appendix. The Internet Appendix contains robustness checks and additional results.³

I. Empirical Results

In this section, we document a robust inverse relation between stock return loadings on the changes in labor market tightness and future equity returns. We establish this result using portfolios sorted by labor market tightness loadings and Fama-MacBeth (1973) regressions.

A. Data

Our sample includes all common stocks (share code of 10 or 11) listed on NYSE, NASDAQ, and Amex (exchange code of 1, 2, or 3) available from CRSP. Availability of labor market data restricts our analysis to the 1951 to 2014 period. We obtain data on book equity and other firm-level attributes from Compustat. In Appendix A, we list the exact formulas for firm characteristics used in our tests.

B. Labor Market Tightness

We obtain monthly labor force participation and unemployment rates from the Current Population Survey of the Bureau of Labor Statistics for the years 1951 to 2014. The traditionally used measure of vacancies is the Conference Board's Help Wanted Index, which was based on advertisements in 51 major newspapers. However, in 2005, the Conference Board replaced this measure with Help Wanted Online, recognizing the importance of online marketing. We therefore follow Barnichon (2010), who combines the print and online data to create a composite vacancy index starting in 1995.⁴

We define labor market tightness as the ratio of aggregate vacancy postings to unemployed workers. The pool of unemployed workers is the product of the unemployment rate and the labor force participation rate (LFPR). Hence, labor market tightness is

$$\theta_t = \frac{\text{Vacancy Index}_t}{\text{Unemployment Rate}_t \times \text{LFPR}_t}. \quad (1)$$

³ The Internet Appendix is available in the online version of the article on the *Journal of Finance* website.

⁴ The data are available on his website, <http://sites.google.com/site/regisbarnichon/>.

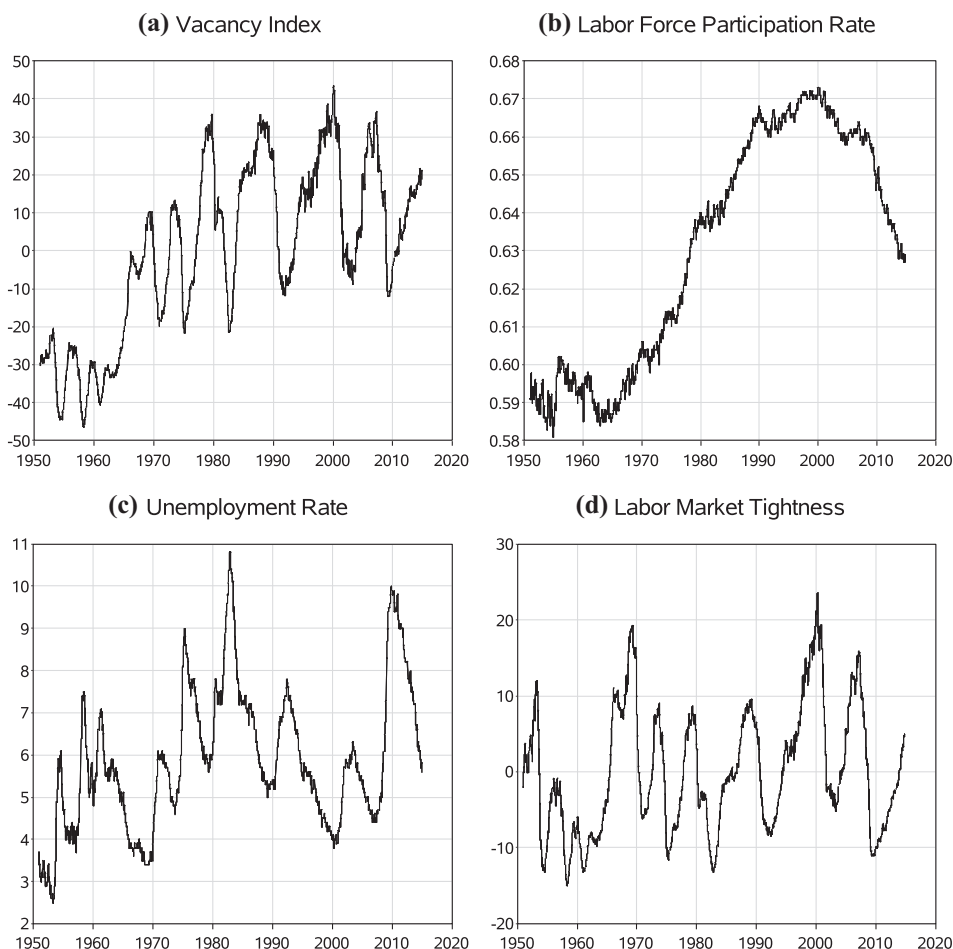


Figure 1. Labor market tightness and its components. This figure plots the monthly time series of the vacancy index, the labor force participation rate, the unemployment rate, and labor market tightness for the years 1951 to 2014.

Figure 1 plots the monthly time series of θ_t and its components. Labor market tightness is strongly procyclical and persistent as in Shimer (2005). The cyclical nature of θ_t is driven by the procyclicality of vacancies—its numerator—and the countercyclicality of the number of unemployed workers—its denominator.

We define the labor market tightness factor in month t as the change in logs of the vacancy-unemployment ratio θ_t :

$$\vartheta_t = \log(\theta_t) - \log(\theta_{t-1}). \quad (2)$$

Table I reports the time-series properties of ϑ_t , its components, and other macro variables. We consider the changes in the Industrial Production Index (IP) from the Board of Governors, the changes in the Consumer Price Index (CPI) from

Table I
Summary Statistics

This table reports statistics for the monthly labor market tightness factor (ϑ), changes in the vacancy index (VAC), changes in the unemployment rate (UNEMP), changes in the labor force participation rate (LFPR), changes in industrial production (IP), changes in the Consumer Price Index (CPI), dividend yield (DY), T-bill rate (TB), term spread (TS), and default spread (DS) for the period 1954 to 2014. Means and standard deviations are in percent.

	Mean	StDev	Correlations								
			ϑ	VAC	UNEMP	LFPR	IP	CPI	DY	TB	TS
ϑ	0.11	5.43									
VAC	0.20	3.27	0.82								
UNEMP	0.08	3.30	-0.83	-0.36							
LFPR	0.01	0.29	-0.13	0.04	0.16						
IP	0.24	0.88	0.54	0.44	-0.47	0.04					
CPI	0.30	0.32	-0.08	-0.07	0.06	0.05	-0.08				
DY	3.15	1.13	-0.15	-0.11	0.13	0.08	-0.10	0.36			
TB	0.37	0.25	-0.13	-0.14	0.07	0.06	-0.08	0.53	0.54		
TS	1.49	1.20	0.11	0.12	-0.06	-0.04	0.04	-0.30	-0.14	-0.41	
DS	0.98	0.45	-0.26	-0.21	0.22	-0.04	-0.28	0.11	0.33	0.31	0.28

the Bureau of Labor Statistics (BLS), the dividend yield of the S&P 500 Index (DY) as computed by Fama and French (1988), the term spread (TS) between 10-year and three-month Treasury constant-maturity yields, and the default spread (DS) between Moody’s Baa and Aaa corporate bond yields.

The labor market tightness factor is more volatile than any of the considered variables. As expected, it is strongly correlated with its components. The factor is also highly correlated with the default spread and the changes in industrial production, which motivates us to conduct robustness tests (described below) to confirm that our results are driven by the changes in labor market tightness rather than by these other variables.

To study the relation between stock return sensitivity to the changes in labor market tightness and future equity returns, we estimate loadings for each stock from a two-factor model based on the market excess return, R_t^M , and labor market tightness, ϑ_t . At the end of each month τ , we run rolling regressions of the form

$$R_{i,t}^e = \alpha_{i,\tau} + \beta_{i,\tau}^M R_t^M + \beta_{i,\tau}^\vartheta \vartheta_t + \varepsilon_{i,t}, \tag{3}$$

where $R_{i,t}^e$ is the excess return on stock i in month $t \in \{\tau - 35, \tau\}$. To obtain meaningful risk loadings at the end of month τ , we require each stock to have valid returns in at least 24 of the last 36 months.⁵

⁵ In Table IA.I of the Internet Appendix, we show that our results are robust to using 24, 48, or 60 months to estimate betas.

Table II
Characteristics of Labor Market Tightness Portfolios

This table reports average characteristics for portfolios of stocks sorted by their loadings on labor market tightness β^θ . β^M denotes the market beta, BM the book-to-market ratio, ME the market equity decile, RU the 12-month run-up return in percent. AG, IK, and HN are asset growth, investment, and new hiring rates, respectively, in percent. LEV is leverage. Mean characteristics are calculated annually for each decile and then averaged over time. The sample period is 1954 to 2014.

Decile	β^θ	β^M	BM	ME	RU	AG	IK	HN	LEV
Low	-0.80	1.36	0.89	4.81	15.85	12.76	32.69	6.21	0.75
2	-0.38	1.16	0.91	5.72	13.90	12.94	29.61	7.30	0.81
3	-0.23	1.06	0.90	6.10	12.93	11.05	27.55	5.60	0.75
4	-0.12	1.02	0.91	6.28	13.24	11.20	26.78	6.71	0.78
5	-0.02	1.00	0.92	6.20	13.57	11.21	26.12	5.06	0.79
6	0.06	1.01	0.93	5.98	13.30	11.19	26.42	5.12	0.77
7	0.16	1.04	0.94	5.83	13.75	11.20	27.40	5.73	0.77
8	0.28	1.09	0.94	5.53	13.59	11.39	28.06	5.49	0.73
9	0.46	1.17	0.93	5.01	14.14	11.90	29.53	6.84	0.77
High	0.92	1.32	0.90	4.01	16.48	12.75	32.96	6.96	0.78

C. Portfolio Sorts

At the end of each month τ , we rank stocks into deciles by loadings on labor market tightness $\beta_{i,\tau}^\theta$, computed from regression (3). We skip a month to allow information on the vacancy and unemployment rates to become publicly available and hold the resulting 10 value-weighted portfolios without rebalancing for one year ($\tau + 2$ through $\tau + 13$, inclusive). Consequently, in month τ each decile contains stocks that were added to that portfolio at the end of $\tau - 13$ through $\tau - 2$. This design is similar to the approach used to construct momentum portfolios and reduces noise due to seasonalities. We show robustness to alternative portfolio formation methods in the next section.

Table II presents average firm characteristics for the resulting decile portfolios. Average loadings on labor market tightness (β^θ) range from -0.80 for the bottom decile to 0.92 for the top decile. While betas of individual stocks are estimated with noise, the noise is smaller at the portfolio level, and we find that average loadings of all β^θ decile portfolios are statistically significantly different from zero. We also find that, for all adjacent deciles, average labor market tightness betas are statistically significantly different.

Table II shows that firms in the high- and low- β^θ groups are on average smaller with higher market betas than firms in the other deciles, as is often the case when firms are sorted on estimated loadings. No strong relation emerges between loadings on labor market tightness and other considered characteristics: book-to-market ratio (BM), stock return run-up (RU), asset growth rate (AG), investment rate (IR), hiring rate (HN), and leverage (LEV). The lack of a relation between loadings on labor market tightness and hiring rates is of particular interest, as it provides the first evidence that separates our empirical results from those of Belo, Lin, and Bazdresch (2014).

Table III
Performance of Labor Market Tightness Portfolios

This table reports average raw returns and alphas, in percent per month, and loadings from four-factor model regressions for the 10 portfolios of stocks sorted on the basis of their loadings on the labor market tightness factor, as well as for the portfolio that is long the low decile and short the high decile. The bottom row gives *t*-statistics for the low-high portfolio. Firms are assigned into deciles at the end of each month and the value-weighted portfolios are held without rebalancing for 12 months. Conditional alphas are based on either Ferson and Schadt (1996, FS) or Boguth et al. (2011, BCFS). The sample period is 1954 to 2014.

Decile	Raw	Unconditional Alphas			Cond. Alphas		Four-Factor Loadings			
	Return	CAPM	3-Factor	4-Factor	FS	BCFS	MKT	HML	SMB	UMD
Low	1.14	0.02	0.04	0.03	0.06	0.06	1.16	−0.10	0.42	0.01
2	1.10	0.11	0.11	0.11	0.09	0.09	1.04	0.02	−0.01	−0.01
3	1.07	0.12	0.09	0.12	0.09	0.09	0.99	0.07	−0.08	−0.03
4	1.02	0.10	0.07	0.07	0.09	0.09	0.96	0.09	−0.09	−0.01
5	1.01	0.09	0.03	0.02	0.05	0.05	0.97	0.14	−0.10	0.01
6	0.98	0.06	0.02	0.00	0.03	0.02	0.97	0.10	−0.11	0.03
7	0.99	0.05	0.03	0.05	0.03	0.03	0.97	0.04	−0.07	−0.01
8	0.97	−0.02	−0.02	0.01	−0.01	0.00	1.02	−0.01	0.05	−0.04
9	0.89	−0.18	−0.16	−0.11	−0.13	−0.11	1.11	−0.09	0.21	−0.05
High	0.66	−0.52	−0.51	−0.41	−0.45	−0.44	1.19	−0.16	0.64	−0.11
Low-High	0.48	0.54	0.55	0.44	0.52	0.50	−0.04	0.05	−0.23	0.12
<i>t</i> -statistic	[3.66]	[4.12]	[4.20]	[3.31]	[3.96]	[3.83]	[−1.23]	[1.09]	[−4.95]	[3.54]

For each decile portfolio, we obtain monthly time series of returns from January 1954 until December 2014. Table III summarizes returns, alphas, and betas for each decile and for the portfolio that is long the decile with low loadings and short the decile with high loadings on labor market tightness. To control for differences in risk across deciles, we present unconditional alphas from the CAPM, Fama and French (1993) three-factor model, and Carhart (1997) four-factor model. We account for possible time-variation in betas and risk premiums by calculating conditional alphas following either Ferson and Schadt (1996, FS) or Boguth et al. (2011, BCFS).⁶ The last four columns of the table show market (MKT), value (HML), size (SMB), and momentum (UMD) betas for each decile. Firms in the high decile have somewhat larger size betas and lower momentum loadings.

Both raw and risk-adjusted returns of the 10 portfolios indicate a strong negative relation between loadings on the labor market tightness factor and

⁶ Specifically, we calculate conditional alphas as intercepts of the regression

$$R_{j,t}^c = \alpha_j + \beta_j [1 \ Z_{t-1}]' R_t^M + e_{j,\tau},$$

where *j* indexes portfolios, *t* indexes months, β_j is a $1 \times (k + 1)$ parameter vector, and Z_{t-1} is a $1 \times k$ instrument vector. The Ferson and Schadt (1996) conditional alpha is computed using as instruments demeaned dividend yield, term spread, T-bill rate, and default spread. The Boguth et al. (2011) conditional alpha is computed by additionally including as instruments lagged 6- and 36-month market returns and average lagged 6- and 36-month betas of the portfolios.

Table IV
Summary Statistics for Risk Factors

This table reports summary statistics for the difference in returns on stocks with low and high loadings β^θ on the labor market tightness factor as well as for the market excess return and the value, size, and momentum factors. All data are monthly. Means and standard deviations are in percent. The sample period is 1954 to 2014.

	Mean	Standard Deviation	Sharpe Ratio	Correlations			
				Low-High β^θ Return	Mkt Excess Return	Value Factor	Size Factor
Low-high β^θ return	0.48	3.56	0.14				
Market excess return	0.60	4.35	0.14	-0.13			
Value factor	0.37	2.73	0.13	0.07	-0.27		
Size factor	0.19	2.94	0.07	-0.21	0.28	-0.21	
Momentum factor	0.72	4.00	0.18	0.13	-0.12	-0.17	-0.03

future stock performance. Firms in the low- β^θ decile earn the highest average return, 1.14% monthly, whereas the high- β^θ decile performs most poorly, generating on average just 0.66% return per month. The difference in the performance of the two deciles, at 0.48%, is economically large and statistically significant (t -statistic of 3.66). The corresponding differences in both unconditional and conditional alphas are similarly striking, ranging from 0.44% (t -statistic of 3.31) for Carhart four-factor alphas to 0.55% (t -statistic of 4.20) for Fama-French three-factor alphas. Conditional alphas are similar in magnitude to unconditional ones, suggesting negligible time-variation in betas.

Results of portfolio sorts thus strongly suggest that loadings on labor market tightness are an important cross-sectional predictor of returns. To evaluate robustness of this relation over time, we plot cumulative returns (Panel A) and monthly returns (Panel B) for the long-short β^θ portfolio in Figure 2. Cumulative returns steadily increase throughout the sample period, indicating that the relation between loadings on labor market tightness and future stock returns persists over time. Table IV presents summary statistics for returns on this portfolio and for market, value, size, and momentum factors. The long-short labor market tightness portfolio is less volatile than the market and momentum factors and achieves a Sharpe ratio (0.14) similar to those of the market and value factors.

We emphasize that although the difference in returns of firms with low and high loadings on labor market tightness cannot be explained by the commonly considered factor models, this difference should not be interpreted as mispricing. It arises rationally in our theoretical framework as compensation for risk associated with labor market frictions. The commonly used factor models such as the CAPM do not capture this type of risk. Consequently, alphas from such models are different for firms with different loadings on labor market tightness.

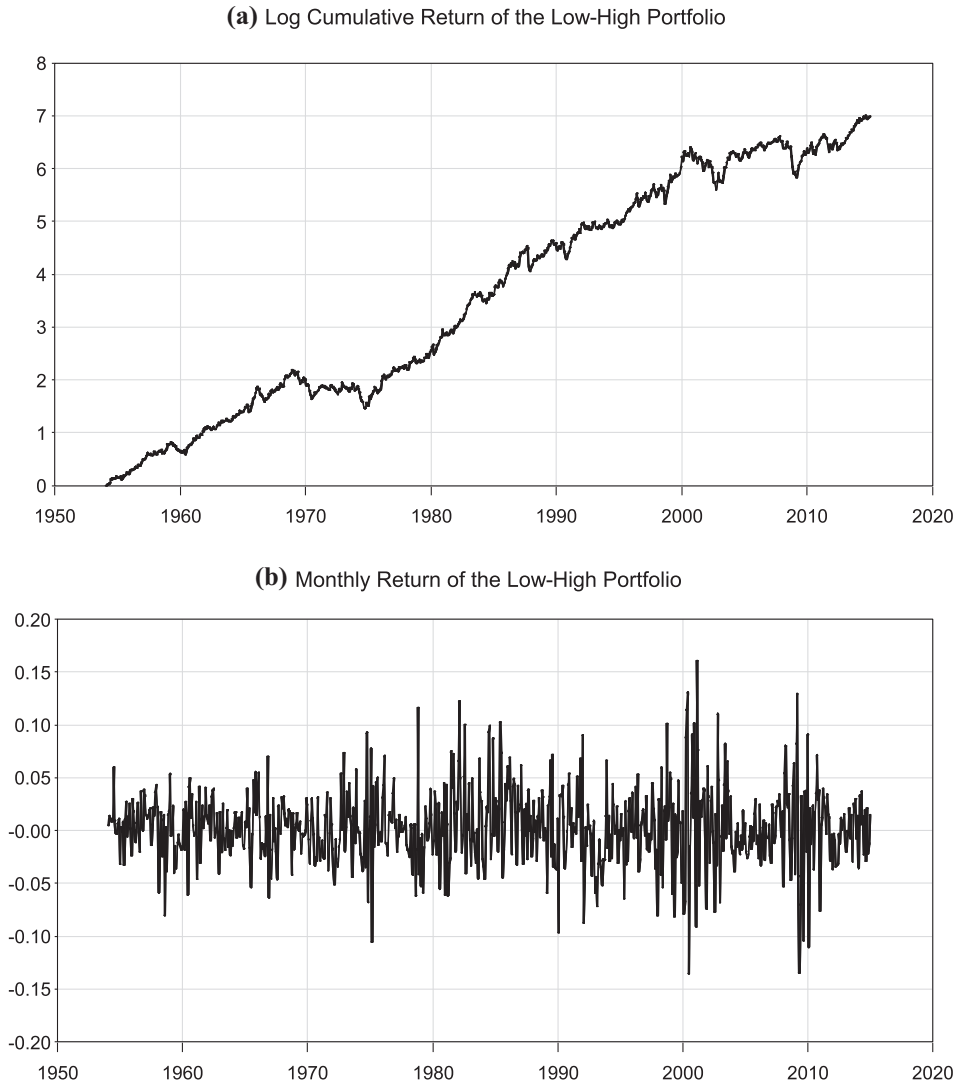


Figure 2. Returns on long-short labor market tightness portfolios. This figure plots the log cumulative (Panel A) and monthly (Panel B) returns on a portfolio that is long the decile of stocks with the lowest exposure to the labor market tightness factor and short the decile of stocks with the highest loadings. The sample spans 1954 to 2014.

D. Robustness of Portfolio Sorts

We now demonstrate robustness of the relation between stock return loadings on the changes in labor market tightness and future equity returns. We use alternative timings of portfolio formation, exclude micro cap stocks, consider modified definitions of the labor market tightness factor, and change regression

(3) to also include size, value, and momentum factors. Table V summarizes the results of the robustness tests.

The portfolio formation design employed in the previous section is motivated by investment strategies such as momentum. It involves holding 12 overlapping portfolios and reduces noise due to seasonalities. We consider two alternatives: forming portfolios only once a year (Panel A) and holding portfolios for one month (Panel B). Both alternatives ensure that no portfolios overlap. Panels A and B of Table V show that each of these approaches results in even more dramatic differences in the future performance of low- and high- β^θ deciles. For example, the difference in average returns of the low and high deciles reaches 0.55% monthly when portfolios are formed once a year, compared to 0.48% reported in Table IV.

We next explore the sensitivity of the results to the length of time between calculating β^θ and forming portfolios. Our base case results in Table IV are obtained by assuming that all variables needed to compute labor market tightness (vacancy index, unemployment rate, and labor force participation rate) are publicly available within a month. This assumption is well justified in current markets, where the data for any given month are typically available within days after the end of that month. To allow for slower dissemination of data in the earlier sample, we consider a two-month waiting period. Panel C of Table V shows that the results are not sensitive to this change in methodology. The difference in the future returns of stocks with low and high loadings on labor market tightness remains at 0.48% per month.

To account for the possibility that the negative relation between stock return loadings on the changes in labor market tightness and future equity returns is driven by stocks with extreme loadings, we check robustness to sorting firms into quintile rather than decile portfolios. Panel D of Table V shows that the difference in the future returns of quintiles with low and high loadings is economically and statistically significant.

In Panel E of Table V we evaluate robustness to excluding microcaps, which we define as stocks with market equity below the 20th NYSE percentile. Microcaps represent on average just 3% of the total market capitalization of all stocks listed on NYSE, NASDAQ, and Amex, but they account for approximately 60% of the total number of stocks and their estimated betas can be noisy. Excluding these stocks from the sample does not meaningfully impact the results.

We also evaluate robustness to two alternative definitions of the labor market tightness factor. Table I shows that ϑ_t as defined in equation (2) is correlated with the changes in industrial production and other macro variables. To ensure that the relation between stock return loadings on the labor market tightness factor and future equity returns is not driven by these variables, our first alternative specification involves redefining the labor market tightness factor as the residual $\tilde{\vartheta}_t$ from the time-series regression

$$\vartheta_t = \gamma_0 + \gamma_1 IP_t + \gamma_2 CPI_t + \gamma_3 DY_t + \gamma_4 TB_t + \gamma_5 TS_t + \gamma_6 DS_t + \tilde{\vartheta}_t, \quad (4)$$

Table V
Performance of Labor Market Tightness Portfolios: Robustness

This table reports average raw returns and alphas, in percent per month, four-factor loadings, and corresponding t -statistics for the portfolio that is long the decile of stocks with low loadings on the labor market tightness factor and short the decile with high loadings. In Panel A, firms are assigned into deciles at the end of May and are held for one year starting in July. In Panel B, firms are assigned into deciles at the end of each month τ and are held during month $\tau + 2$. In Panel C, firms are assigned into deciles at the end of each month τ and are held without rebalancing for 12 months beginning in month $\tau + 3$. In Panel D, firms are assigned into quintiles rather than deciles. In Panel E, firms below the 20th percentile of NYSE market capitalization are excluded from the sample. In Panel F, the labor market tightness factor is defined as the residual from a time-series regression of the log changes in labor market tightness on changes in industrial production, Consumer Price Index, dividend yield, T-bill rate, term spread, and default spread. In Panel G, the labor market tightness factor is defined as the residual from an ARMA(1,1) specification. In Panel H, regression (3) is amended to also include size, value, and momentum factors. Conditional alphas are based on either Ferson and Schadt (1996, FS) or Boguth et al. (2011, BCFS). In all panels, portfolios are value-weighted. t -statistics are in square brackets. The sample period is 1954 to 2014.

Decile	Raw	Unconditional Alphas			Cond. Alphas		Four-Factor Loadings			
	Return	CAPM	3-Factor	4-Factor	FS	BCFS	MKT	HML	SMB	UMD
Panel A: Nonoverlapping portfolios										
Low-High	0.55	0.60	0.53	0.45	0.52	0.51	0.01	0.23	−0.25	0.08
t -statistic	[3.52]	[3.84]	[3.39]	[2.81]	[3.34]	[3.26]	[0.19]	[3.82]	[−4.59]	[2.15]
Panel B: One-month holding period										
Low-High	0.54	0.63	0.67	0.55	0.58	0.57	−0.07	−0.01	−0.28	0.13
t -statistic	[3.26]	[3.75]	[4.01]	[3.21]	[3.66]	[3.56]	[−1.79]	[−0.10]	[−4.74]	[3.13]
Panel C: Two-month waiting period										
Low-High	0.48	0.54	0.55	0.44	0.51	0.50	−0.04	0.05	−0.22	0.12
t -statistic	[3.70]	[4.15]	[4.22]	[3.30]	[3.97]	[3.84]	[−1.16]	[1.10]	[−4.83]	[3.64]
Panel D: Quintile portfolios										
Low-High	0.30	0.36	0.36	0.30	0.32	0.30	−0.07	0.07	−0.20	0.07
t -statistic	[2.64]	[3.35]	[3.31]	[2.61]	[2.97]	[2.77]	[−2.58]	[1.73]	[−5.33]	[2.70]
Panel E: Excluding micro caps										
Low-High	0.43	0.47	0.48	0.33	0.46	0.44	−0.05	0.03	0.00	0.15
t -statistic	[3.75]	[4.05]	[4.05]	[2.80]	[4.02]	[3.83]	[−1.95]	[0.74]	[−0.10]	[5.30]
Panel F: Alternative definition 1 of ϑ										
Low-High	0.48	0.54	0.55	0.50	0.52	0.51	−0.06	0.03	−0.19	0.05
t -statistic	[3.55]	[3.99]	[4.05]	[3.60]	[3.93]	[3.85]	[−1.79]	[0.66]	[−4.09]	[1.56]
Panel G: Alternative definition 2 of ϑ										
Low-High	0.46	0.53	0.53	0.42	0.48	0.47	−0.04	0.08	−0.21	0.11
t -statistic	[3.50]	[3.87]	[3.86]	[3.05]	[3.60]	[3.49]	[−1.22]	[1.48]	[−4.50]	[3.17]
Panel H: Alternative computation of β^θ										
Low-High	0.30	0.37	0.39	0.30	0.34	0.32	−0.06	0.03	−0.07	0.20
t -statistic	[2.53]	[3.04]	[3.17]	[2.62]	[2.83]	[2.69]	[−2.18]	[0.72]	[−1.65]	[6.73]

where IP_t , CPI_t , DY_t , TB_t , TS_t , and DS_t are the changes in industrial production, the changes in the Consumer Price Index, the dividend yield, the T-bill rate, the term spread, and the default spread, respectively. For our second alternative definition, we compute the labor market tightness factor as the residual from an ARMA(1,1) specification.

The disadvantage of both of these approaches is that they introduce look-ahead bias as the entire sample is used to estimate the labor market tightness factor. However, the first alternative definition allows us to focus on the component of labor market tightness that is unrelated to macro variables that may have nonzero prices of risk, while the second definition allows us to focus on the unpredictable component of labor market tightness. Panels F and G of Table V show that our results are little affected by these changes in the definition of the labor market tightness factor. The differences in the future returns of portfolios with low and high loadings on the factor are always statistically significant and economically important, ranging between 0.42% and 0.55% monthly.

In Table IV, we compute alphas from multifactor models to ensure that the relation between loadings on labor market tightness and future equity returns is not driven by differences in loadings on known risk factors. For robustness, we also consider modifying regression (3) to include size, value, and momentum factors. Panel H of Table V shows that our results remain strong when using this alternative method to estimate β^θ .

We provide additional robustness tests in the Internet Appendix. In Table IA.I, we consider different beta estimation windows. In Tables IA.II and IA.III, we control for the liquidity and profitability factors, and summarize postranking β^θ loadings of the decile portfolios. We also show in Table IA.IV that the relation between loadings on labor market tightness and future equity returns holds irrespective of the level of stocks' market betas β^M .

E. Fama-MacBeth Regressions

The empirical evidence from portfolio sorts provides a strong indication of an inverse relation between stock return loadings on the changes in labor market tightness and subsequent equity returns. However, such univariate analysis does not account for other firm-level characteristics previously shown to relate to future returns. We now compare the loadings on the labor market tightness factor with other well-established determinants of the cross-section of stock returns. Our goal is to evaluate whether the ability of β^θ to forecast returns is subsumed by other firm-level characteristics. To this end, we run monthly Fama-MacBeth (1973) regressions of stock excess returns on lagged β^θ and β^M computed from regression (3) and on control variables.

We include as controls commonly considered firm characteristics such as log market capitalization (ME), log book-to-market (BM), and the return run-up (RU) (Fama and French (1992) and Jegadeesh and Titman (1993)). We also consider recently documented determinants of the cross-section of stock returns, including the investment rate (IK) of Titman, Wei, and Xie (2004), asset growth rate (AG) of Cooper, Gulen, and Schill (2008), and labor hiring rate

Table VI
Fama-MacBeth Regressions of Monthly Stock Returns

This table reports results of Fama-MacBeth (1973) regressions of monthly stock returns, in percent, on lagged labor market tightness loadings (β^θ), market betas (β^M), log market equity (ME), log book equity to market equity (BM), 12-month stock returns (RU), hiring rates (HN), investment rates (IK), and asset growth rates (AG). Reported are average coefficients and the corresponding Newey and West (1987) t -statistics in square brackets. Variable definitions are in Appendix A. The sample period is 1954 to 2014.

Reg	β^θ	β^M	ME	BM	RU	HN	IK	AG
(1)	−0.21 [−2.26]	−0.08 [−0.76]						
(2)	−0.26 [−2.76]	−0.07 [−0.72]	−0.11 [−3.19]					
(3)	−0.25 [−2.65]	−0.01 [−0.12]	−0.09 [−2.40]	0.19 [3.33]				
(4)	−0.37 [−3.77]	−0.02 [−0.21]	−0.09 [−2.54]	0.20 [3.70]	0.36 [2.61]			
(5)	−0.36 [−3.66]	−0.05 [−0.44]	−0.08 [−2.24]	0.20 [3.33]	0.37 [2.73]	−0.33 [−2.83]		
(6)	−0.36 [−3.61]	−0.02 [−0.25]	−0.09 [−2.63]	0.20 [3.52]	0.36 [2.74]		−0.03 [−1.18]	
(7)	−0.37 [−3.66]	−0.02 [−0.22]	−0.09 [−2.50]	0.17 [2.93]	0.36 [2.64]			−0.52 [−3.08]
(8)	−0.35 [−3.50]	−0.06 [−0.61]	−0.09 [−2.25]	0.18 [2.81]	0.39 [2.99]	−0.13 [−0.71]	0.16 [0.72]	−0.52 [−2.59]

(HN) of Belo, Lin, and Bazdresch (2014). The timing of the variables’ measurement follows the widely accepted convention of Fama and French (1992). Asparouhova, Bessembinder, and Kalcheva (2010) point out that estimates from monthly Fama-MacBeth (1973) regressions are biased due to microstructure noise in security prices. We use the weighted least squares with market capitalizations as weights rather than the ordinary least squares estimation.

Table VI summarizes the results of the Fama-MacBeth (1973) regressions. The coefficient on β^θ is negative and statistically significant in each considered specification, even after accounting for other predictors of the cross-section of equity returns. The magnitude of the coefficient implies that, for a one-standard-deviation increase in β^θ (0.49), subsequent annual returns decline by at least 1.2%.

The changes in labor market tightness are highly correlated with its components and with the changes in industrial production (see Table I). To ensure that our results are not driven by these macro variables, we estimate loadings from a two-factor regression of stock excess returns on market excess returns and log changes in the labor force participation rate, unemployment rate, vacancy index, or industrial production. Tables IA.V and IA.VI of the Internet Appendix show that none of the considered loadings are robustly related to future equity returns, suggesting that the relation between loadings on the labor market tightness factor and future stock returns is not driven by one

particular component of labor market tightness or by the changes in industrial production.

II. Model

The goal of this section is to provide an economic model that explains the empirical link between labor market frictions and the cross-section of equity returns. To this end, we solve a partial equilibrium labor market model and study its implications for stock returns. For tractability we do not model endogenous labor supply decisions from households; instead we assume an exogenous pricing kernel.

A. Revenue

To focus on labor frictions, we abstract from capital accumulation and investment frictions and assume that the only input to production is labor. Firms generate revenue, $Y_{i,t}$, according to a decreasing returns to scale production function

$$Y_{i,t} = e^{x_t + z_{i,t}} N_{i,t}^\alpha, \quad (5)$$

where α denotes the labor share of production and $N_{i,t}$ is the size of the firm's workforce. Both the aggregate productivity shock x_t and the idiosyncratic productivity shocks $z_{i,t}$ follow AR(1) processes

$$x_t = \rho_x x_{t-1} + \sigma_x \varepsilon_t^x, \quad (6)$$

$$z_{i,t} = \rho_z z_{i,t-1} + \sigma_z \varepsilon_{i,t}^z, \quad (7)$$

where $\varepsilon_t^x, \varepsilon_{i,t}^z$ are standard normal i.i.d. innovations. Firm-specific shocks are independent across firms, and from aggregate shocks.

Firm-level workforce dynamics are determined by optimal hiring and firing policies. Firms can expand their workforce by posting vacancies, $V_{i,t}$, to attract unemployed workers. The key friction of labor markets is that not all posted vacancies are filled in a given period. Instead, the rate q at which vacancies are filled is endogenously determined in equilibrium and depends on the tightness of the labor market, θ_t , and an exogenous efficiency shock, p_t , to the matching technology. Firms can also downsize by laying off $F_{i,t}$ workers. Before hiring and firing takes place, a constant fraction s of workers quit voluntarily. Taken together, this implies the following law of motion for a firm's workforce size:

$$N_{i,t+1} = (1 - s)N_{i,t} + q(\theta_t, p_t)V_{i,t} - F_{i,t}. \quad (8)$$

The matching efficiency shock p_t follows an AR(1) process with autocorrelation ρ_p and i.i.d. normal innovations ε_t^p :

$$p_t = \rho_p p_{t-1} + \sigma_p \varepsilon_t^p. \quad (9)$$

Matching efficiency innovations are uncorrelated with aggregate productivity innovations. The matching efficiency shock is common across firms and thus represents aggregate risk. This shock was first studied by Andolfatto (1996), who argues that it can be interpreted as a reallocative shock that is distinct from disturbances that affect production technologies. In search models, the efficiency of the economy's allocative mechanism is captured by the technological properties of the aggregate matching function. Changes in this function can be thought of as reflecting mismatches in the labor market between the skills, geographical location, demography, or other dimensions of unemployed workers and job openings across sectors, thereby causing a shift in the so-called aggregate Beveridge curve.

Several recent studies empirically analyze sources of changes in matching efficiency. Using microdata, Barnichon and Figura (2015) show that fluctuations in matching efficiency can be related to the composition of the unemployment pool, such as an increase in the share of long-term unemployed or fluctuations in participation due to demographic factors, and to dispersion in labor market conditions. Herz and van Rens (2016) and Sahin et al. (2014) highlight the role of skill and occupational mismatch between jobs and workers. Sterk (2015) focuses on geographical mismatch exacerbated by house price movements. And Fujita (2011) analyzes the role of reduced worker search intensity due to extended unemployment benefits.

B. Matching

Labor market tightness affects how easily vacant positions can be filled. It is a function of aggregate vacancy postings and employment. The aggregate number of vacancies, \bar{V} , and aggregate employment, \bar{N} , are the sums of all firm-level vacancies and employment, respectively, that is,

$$\bar{V}_t = \int V_{i,t} d\mu_t \quad \bar{N}_t = \int N_{i,t} d\mu_t, \quad (10)$$

where μ_t denotes the time-varying distribution of firms over the firm-level state space $(z_{i,t}, N_{i,t})$.

The mass of firms is normalized to one. The labor force with mass L is defined as the sum of employed and unemployed. Hence, the unemployment rate is given by $(L - \bar{N})/L$. The mass of the labor force searching for a job includes workers who have just voluntarily quit, $sN_{i,t}$, and is given by

$$\bar{U}_t = L - (1 - s)\bar{N}_t. \quad (11)$$

Labor market tightness can now be defined as the ratio of aggregate vacancies to the mass of the labor force searching for a job, that is, $\theta_t = \bar{V}_t/\bar{U}_t$.

Following den Haan, Ramey, and Watson (2000), vacancies are filled according to a constant returns to scale matching function

$$\mathcal{M}(\bar{U}_t, \bar{V}_t, p_t) = \frac{e^{p_t} \bar{U}_t \bar{V}_t}{(\bar{U}_t^\xi + \bar{V}_t^\xi)^{1/\xi}}, \quad (12)$$

and the rate q at which vacancies are filled per unit of time can be computed from

$$q(\theta_t, p_t) = \frac{\mathcal{M}(\bar{U}_t, \bar{V}_t, p_t)}{\bar{V}_t} = e^{p_t} \left(1 + \theta_t^\xi\right)^{-1/\xi}. \quad (13)$$

The matching rate decreases in θ , meaning that an increase in the relative scarcity of unemployed workers relative to job vacancies makes it more difficult for firms to fill a vacancy. This rate increases in p , as a positive efficiency shock makes finding a worker easier.⁷

C. Wages

In equilibrium, the matching of unemployed workers and firms is imperfect, which results in both equilibrium unemployment and rents. These rents are shared between a firm and its workforce according to a Nash bargaining wage rate. Following Stole and Zwiebel (1996), we assume Nash bargaining wages in multiworker firms with decreasing returns to scale production technology. Specifically, firms renegotiate wages every period with their workforce based on individual (and not collective) Nash bargaining.

In the bargaining process, workers have bargaining weight $\eta \in (0, 1)$. If workers decide not to work, they receive unemployment benefits b , which represents the value of their outside option. They are also rewarded the saving of hiring costs that firms would otherwise incur when posting a job, $\kappa_h \theta_t$, where κ_h is the unit cost of vacancy postings. As a result, wages are given by

$$w_{i,t} = \eta \left[\frac{\alpha}{1 - \eta(1 - \alpha)} \frac{Y_{i,t}}{N_{i,t}} + \kappa_h \theta_t \right] + (1 - \eta)b. \quad (14)$$

Firms benefit from hiring the marginal worker not only through an increase in output by the marginal product of labor but also through a decrease in wage payment to its current workers, $Y_{i,t}/N_{i,t}$. The term $\alpha/(1 - \eta(1 - \alpha))$ represents a reduction in wages coming from decreasing returns to scale. At the same time, workers can extract higher wages from firms when the labor market is tighter. Unemployment benefits provide a floor to wages.⁸

⁷ In the Internet Appendix, we build on Lubik (2009) and estimate matching efficiency shocks as residuals from a fitted nonlinear Beveridge curve of vacancy and unemployment. We find that our empirical results are qualitatively similar when using these estimated shocks instead of log changes in labor market tightness to calculate loadings β^θ .

⁸ The same wage process is used in Elsby and Michaels (2013) and Fujita and Nakajima (2016). See the first paper for a proof.

D. Firm Value

We do not model the supply side of labor coming from households, as this would require solving a full general equilibrium model. Instead, following Berk, Green, and Naik (1999), we specify an exogenous pricing kernel and assume that both the aggregate productivity shock x_t and the efficiency shock p_t are priced. The log of the pricing kernel M_{t+1} is given by

$$m_{t+1} = -r_f - \gamma_x \varepsilon_{t+1}^x - \frac{1}{2} \gamma_x^2 - \gamma_p \varepsilon_{t+1}^p - \frac{1}{2} \gamma_p^2, \quad (15)$$

where r_f denotes the log risk-free rate, γ_x the price of the risk of aggregate productivity shocks, and γ_p the price of the risk of matching efficiency shocks. The risk-free rate is set to be constant. This parsimonious setting allows us to focus on risk premia as the main driver of the model results.

The objective of firms is to maximize their value $S_{i,t}$ either by posting vacancies $V_{i,t}$ to hire workers or by firing $F_{i,t}$ workers to downsize.⁹ Both adjustments are costly at rates κ_h for hiring and κ_f for firing. Firms also pay fixed operating costs f . Dividends to shareholders are given by revenues net of operating, hiring, firing, and wage costs,

$$D_{i,t} = Y_{i,t} - f - \kappa_h V_{i,t} - \kappa_f F_{i,t} - w_{i,t} N_{i,t}. \quad (16)$$

The firm's Bellman equation solves

$$S_{i,t} = \max_{V_{i,t} \geq 0, F_{i,t} \geq 0} \{D_{i,t} + \mathbb{E}_t [M_{t+1} S_{i,t+1}]\}, \quad (17)$$

subject to equations (5) to (16). Notice that the firm's problem is well defined given labor market tightness θ_t and expectations about its dynamics.

E. Equilibrium

In search and matching models, optimal firm employment policies depend on the dynamics of the aggregate labor market. This is typically not the case for models with labor adjustment costs based on Q -theory. Rather, in our setup firms have to know how congested labor markets are when they decide about optimal hiring policies, as next period's workforce, given by equation (8), depends on aggregate labor market tightness θ via the vacancy filling rate q . At the same time, labor market tightness depends on the distribution of vacancy postings implied by the firm-level distribution μ_t and by the aggregate shocks.

Equilibrium in the labor market requires that the beliefs about labor market tightness are consistent with the realized equilibrium. Consequently, the firm-level distribution enters the state space, which is given by

⁹ In contrast to Belo, Lin, and Bazdresch (2014), we do not model time-variation in the flow costs of hiring or firing. Even though such cost shocks would also affect the cash flow of firms, they would not be able to generate the observed dynamics in the labor market, such as shifts in the Beveridge curve.

$\Omega_{i,t} = (N_{i,t}, z_{i,t}, x_t, p_t, \mu_t)$, and labor market tightness θ_t at each date is determined as a fixed point satisfying

$$\theta_t = \frac{\int V(\Omega_{i,t}) d\mu_t}{\bar{U}_t}. \quad (18)$$

This assumes that each individual firm is atomistic and takes labor market tightness as exogenous.

Let Γ be the law of motion for the time-varying firm-level distribution μ_t such that

$$\mu_{t+1} = \Gamma(\mu_t, x_{t+1}, x_t, p_{t+1}, p_t). \quad (19)$$

The recursive competitive equilibrium is characterized by (i) labor market tightness θ_t , (ii) optimal firm policies $V(\Omega_{i,t})$, $F(\Omega_{i,t})$, and firm value function $S(\Omega_{i,t})$, and (iii) a law of motion Γ for the firm-level distribution μ_t such that (a) Optimality: given the pricing kernel (15), Nash bargaining wage rate (14), and labor market tightness θ_t , $V(\Omega_{i,t})$ and $F(\Omega_{i,t})$ solve the firm's Bellman equation (17), where $S(\Omega_{i,t})$ is its solution, and (b) Consistency: θ_t is consistent with the labor market equilibrium (18), and the law of motion Γ for the firm-level distribution μ_t is consistent with the optimal firm policies $V(\Omega_{i,t})$ and $F(\Omega_{i,t})$.

F. Approximate Aggregation

The firm's hiring and firing decisions trade off current costs and future benefits, which depend on the aggregation and evolution of the firm-level distribution μ_t . Rather than solving for the high-dimensional firm-level distribution exactly, we follow Krusell and Smith (1998) and approximate it with one moment. In this partial equilibrium search model, labor market tightness θ_t is a sufficient statistic to solve the firm's problem (17) and thus enters the state vector replacing μ_t ,¹⁰ that is, the sufficient state space is $\hat{\Omega}_{i,t} = (N_{i,t}, z_{i,t}, x_t, p_t, \theta_t)$.

To approximate the law of motion Γ , equation (19), we assume a log-linear functional form

$$\log(\theta_{t+1}) = \tau_0 + \tau_\theta \log(\theta_t) + \tau_x \varepsilon_{t+1}^x + \tau_p \varepsilon_{t+1}^p. \quad (20)$$

Under rational expectations, the perceived labor market outcome equals the realized one at each date of the recursive competitive equilibrium. In equilibrium, we can express the labor market tightness factor ϑ as the log changes in labor market tightness,

$$\vartheta_{t+1} = \tau_0 + (\tau_\theta - 1) \log(\theta_t) + \tau_x \varepsilon_{t+1}^x + \tau_p \varepsilon_{t+1}^p. \quad (21)$$

¹⁰ From the firm's Bellman equation (17), for a given pricing kernel and aggregate shocks, labor market tightness θ_t is the only endogenous aggregate state that affects firm cash flows. If firms can forecast how labor market tightness evolves over time, they do not need to keep track of the evolution of the firm-level distribution.

This definition is consistent with our empirical exercise in Section I.

Our application of Krusell and Smith (1998) differs from Zhang (2005) along two dimensions. First, future labor market tightness θ_{t+1} is a function of the firm distribution at time $t + 1$; hence, it is not in the information set of date t . The forecasting rule (20) at time t does not enable firms to learn θ_{t+1} perfectly, but rather to form a rational expectation about θ_{t+1} . In contrast, Zhang (2005) assumes that firms can perfectly forecast next period's industry price given time t information. If firms could perfectly forecast next period's labor market tightness, it would not carry a risk premium. Second, at each period of the simulation, we impose labor market equilibrium by solving θ_t as the fixed point in equation (18). Hence, there is no discrepancy between the perceived and the realized thetas.

G. Equilibrium Risk Premia

The model is driven by two aggregate shocks: productivity and matching efficiency. To test the model's cross-sectional return implications on the data, it is convenient to derive an approximate log-linear pricing model. Given a log-linear approximation of the pricing kernel (15), expected excess returns obey a two-factor structure such that

$$\mathbb{E}_t [R_{i,t+1}^e] = \beta_{i,t}^x \lambda^x + \beta_{i,t}^p \lambda^p, \quad (22)$$

where expected excess returns are defined as $-\text{Cov}_t(m_{t+1}, R_{i,t+1}^e)$, $\beta_{i,t}^x$ and $\beta_{i,t}^p$ are loadings on aggregate productivity and matching efficiency shocks, and λ^x and λ_t^p are their respective factor risk premia. All proofs of this section are contained in Appendix I.B.

Both aggregate productivity and matching efficiency are not directly observable in the data. Since we would like to take the model to the data, it is necessary to express expected excess returns in terms of observable variables such as the return on the market and labor market tightness. To this end, we also model the market excess return, R_{t+1}^M , as an affine function of the aggregate shocks

$$R_{t+1}^M = \nu_0 + \nu_x \varepsilon_{t+1}^x + \nu_p \varepsilon_{t+1}^p. \quad (23)$$

As a result, we can show that expected excess returns obey a two-factor structure in the market excess return and the log changes in labor market tightness, which is summarized in the following proposition.

PROPOSITION 1: *Given the laws of motion for labor market tightness (21) and the market excess return (23), the log pricing kernel can be expressed as a function of the market excess return and the log changes in labor market tightness, implying a two-factor structure for expected excess returns in the form*

$$\mathbb{E}_t [R_{i,t+1}^e] = \beta_{i,t}^M \lambda^M + \beta_{i,t}^\theta \lambda^\theta, \quad (24)$$

where $\beta_{i,t}^M$ and $\beta_{i,t}^\theta$ are the loadings on the market excess return and the log changes in labor market tightness

$$\beta_{i,t}^M = \frac{\tau_p}{\tau_p v_x - \tau_x v_p} \beta_{i,t}^x + \frac{-\tau_x}{\tau_p v_x - \tau_x v_p} \beta_{i,t}^p \quad (25)$$

$$\beta_{i,t}^\theta = \frac{-v_p}{\tau_p v_x - \tau_x v_p} \beta_{i,t}^x + \frac{v_x}{\tau_p v_x - \tau_x v_p} \beta_{i,t}^p \quad (26)$$

and λ^M and λ^θ are the respective factor risk premia, given by

$$\lambda^M = v_x \lambda^x + v_p \lambda^p \quad \lambda^\theta = \tau_x \lambda^x + \tau_p \lambda^p. \quad (27)$$

We call relation (24) the Labor Capital Asset Pricing Model.¹¹ The goal of the model is to endogenously generate a negative factor risk premium of labor market tightness, λ^θ . We explain the intuition behind Proposition 1 after the calibration in Section III.C.

In the data, the CAPM cannot explain the returns of portfolios sorted by loadings on labor market tightness, $\beta_{i,t}^\theta$. To replicate this failure of the CAPM in the model, we can compute a misspecified one-factor CAPM and compare the CAPM-implied alphas with the data. The following proposition summarizes this idea.

PROPOSITION 2: *Given the laws of motion for labor market tightness (21) and the market excess return (23), the CAPM implies a linear pricing model of the form*

$$\mathbb{E}_t [R_{i,t+1}^e] = \alpha_{i,t}^{CAPM} + \beta_{i,t}^{CAPM} \lambda^{CAPM}, \quad (28)$$

where the CAPM factor risk premium $\lambda^{CAPM} = v_0$. The CAPM mispricing alphas are given by

$$\alpha_{i,t}^{CAPM} = \left(\lambda^x - \frac{v_0 v_x}{v_x^2 + v_p^2} \right) \beta_{i,t}^x + \left(\lambda^p - \frac{v_0 v_p}{v_x^2 + v_p^2} \right) \beta_{i,t}^p, \quad (29)$$

and CAPM loadings on the market return by

$$\beta_{i,t}^{CAPM} = \frac{v_x \beta_{i,t}^x + v_p \beta_{i,t}^p}{v_x^2 + v_p^2}. \quad (30)$$

Intuitively, a one-factor model, such as the CAPM, cannot span two independent sources of aggregate risk, causing measured mispricing alphas. This insight is qualitatively in line with the empirical findings above and are confirmed quantitatively next.

¹¹ Note that the risk loadings (25) and (26) are not univariate regression betas because the market return and labor market tightness are correlated.

Table VII
Benchmark Parameter Calibration

This table lists the parameter values for the benchmark calibration, which is at the monthly frequency.

Parameter	Symbol	Value
<i>Labor Market</i>		
Size of the labor force	L	1.55
Matching function elasticity	ξ	1.27
Bargaining power of workers	η	0.115
Benefit of being unemployed	b	0.71
Returns to scale of labor	α	0.75
Workers quit rate	s	0.022
Flow cost of vacancy posting	κ_h	0.8
Flow cost of firing	κ_f	0.4
Fixed operating costs	f	0.275
<i>Shocks</i>		
Persistence of aggregate productivity shock	ρ_x	0.983
Volatility of aggregate productivity shock	σ_x	0.007
Persistence of matching efficiency shock	ρ_p	0.958
Volatility of matching efficiency shock	σ_p	0.029
Persistence of idiosyncratic productivity shock	ρ_z	0.965
Volatility of idiosyncratic productivity shock	σ_z	0.095
<i>Pricing Kernel</i>		
Risk-free rate	r_f	0.001
Price of risk of aggregate productivity shock	γ_x	0.28
Constant price of risk of matching efficiency shock	γ_p	-1.015

III. Quantitative Results

In this section, we first describe our calibration strategy and present the numerical results on the equilibrium forecasting rules. Given the equilibrium dynamics for the labor market, we then calculate loadings on labor market tightness and show that the model is consistent with the inverse relation between loadings and future stock returns in the cross-section. We solve the competitive equilibrium numerically on the discretized state space $\tilde{\Omega}_{i,t}$, using an iterative algorithm described in Appendix C.

A. Calibration

Table VII summarizes the parameter calibration of the benchmark model. Labor and equity market data are available monthly, and we use this frequency for the calibration.

The labor literature provides several empirical studies to calibrate labor market parameters. Following Elsby and Michaels (2013) and Fujita and Nakajima (2016), we scale the size of labor force L to match the average unemployment rate. The elasticity of the matching function determines the responsiveness of the vacancy filling rate to the changes in labor market tightness. Based on

the structural estimate in den Haan, Ramey, and Watson (2000), we set the elasticity ξ at 1.27.

The bargaining power of workers η determines the rigidity of wages over the business cycle. As emphasized by Hagedorn and Manovskii (2008) and Gertler and Trigari (2009), aggregate wages are half as volatile as labor productivity. We follow their calibration strategy and set $\eta = 0.115$ to match the relative volatility of wages to output.¹² It is important to highlight that our model is not driven by sticky wages as proposed by Hall (2005) and Gertler and Trigari (2009). In our model, wages are less volatile than productivity but, conditional on productivity, they are not sticky. This feature is consistent with Pissarides (2009), who argues that Nash bargaining wage rates are in line with wages for new hires.

If workers decide not to work, they receive the flow value of unemployment activities b . Shimer (2005) argues that the outside option for rejecting a job offer are unemployment benefits and thus sets b to 0.4. Hagedorn and Manovskii (2008), in contrast, claim that unemployment activities capture not only unemployment benefits but also utility from home production and leisure. They calibrate b close to one. As in the calibration of Pissarides (2009), we follow Hall and Milgrom (2008) and set the value of unemployment activities to 0.71.¹³

The labor share of income, which Gomme and Rupert (2007) estimate to be around 0.72, is highly affected by the value of unemployment activities b and the output elasticity of labor α . Since the value of unemployment activities is close to the labor share of income, we can easily match the labor share by setting α to 0.75. We assume less curvature in the production function than, for instance, Cooper, Haltiwanger, and Willis (2007). However, they do not model wages as the outcome of Nash bargaining.

Motivated by Davis, Faberman, and Haltiwanger (2006), we use the flows in the labor market as measured in the Job Openings and Labor Turnover Survey (JOLTS) collected by the Bureau of Labor Statistics to calibrate the monthly separation rate s , as well as the proportional hiring κ_h and firing κ_f costs. JOLTS provides monthly data on the rates of hires, separations, quits, and layoffs.

The total separation rate captures both voluntary quits and involuntary layoffs. As firms in our model can optimize over the number of workers to be laid off, we calibrate the separation rate only to the voluntary quit rate, which captures workers switching jobs due to, for instance, career development reasons, better pay, or improved working conditions. As such, we set the monthly exogenous quit rate s to 2.2%.

The proportional costs of hiring and firing workers, κ_h and κ_f , determine both the overall costs of adjusting the workforce as well as the behavior of firm policies. Since the literature provides little guidance on estimates of hiring

¹² Hagedorn and Manovskii (2008) set the bargaining power of workers at 0.054 and Lubik (2009) estimates it to be 0.03.

¹³ Similarly, Lubik (2009) estimates that unemployment activities amount to 0.74 relative to unit mean labor productivity.

costs, we set κ_h to 0.8 to match the aggregate hiring rate of workers, defined as the ratio of aggregate filled vacancies to the employed labor force, $q_t \bar{V}_t / \bar{N}_t$. As hiring costs increase, firms post fewer vacancies, so the hiring rate rises. Our parameter choice is close to Hall and Milgrom (2008), who account for both the capital costs of vacancy creation and the opportunity cost of labor effort devoted to hiring activities.

Employment protection legislation comprises a set of rules and restrictions governing the dismissals of employees. Such provisions impose a firing cost on firms along two dimensions: a transfer from the firm to the worker who is laid off (e.g., severance payments), and a tax to be paid outside the job-worker pair (e.g., legal expenses). As the labor search literature does not provide guidance on the magnitude of this parameter, we set the flow costs of firing workers κ_f to 0.4 to match the aggregate layoff rate, defined as the ratio of total laid off workers to the employed labor force, \bar{F}_t / \bar{N}_t . As firing costs increase, firms lay off fewer workers, so the firing rate drops.

The last cost parameter is fixed operating costs f . Without these costs, the model would overstate firms' net profit margin. Consequently, we target the aggregate profit to aggregate output ratio to calibrate f .

We calibrate the two aggregate shocks following the macroeconomics literature. Since labor is the only input to production, aggregate productivity is typically measured as aggregate output relative to the labor hours used in the production of that output. As such, labor productivity is more volatile than total factor productivity. Similar to Gertler and Trigari (2009), we set $\rho_x = 0.95^{1/3}$ and $\sigma_x = 0.007$. Shocks to the matching efficiency tend to be less persistent but more volatile than labor productivity shocks. For instance, Andolfatto (1996) estimates matching shocks to have persistence of 0.85 with innovation volatility of 0.07 at the quarterly frequency. We use more recent estimates by Chermukhin and Restrepo-Echavarria (2014) and set $\rho_p = 0.88^{1/3}$ and $\sigma_p = 0.029$.¹⁴ For the persistence ρ_z and conditional volatility σ_z of firm-specific productivity, we choose values close to those in Zhang (2005), Gomes and Schmid (2010), and Fujita and Nakajima (2016) to match the cross-sectional properties of firm employment policies.

The pricing kernel is calibrated to match financial moments. We choose the constant risk-free rate r_f and the pricing kernel parameters γ_x and γ_p so that the model approximately matches the averages of the risk-free rate and market return. This requires that $r_f = 0.001$, $\gamma_x = 0.28$, and $\gamma_p = 1.015$. Importantly, shocks to matching efficiency carry a negative price of risk.

Berk, Green, and Naik (1999) provide a motivation for $\gamma_x > 0$ in an economy with only aggregate productivity shocks. The assumption of $\gamma_p < 0$ can be motivated as follows. In a general equilibrium economy with a representative household, a positive matching efficiency shock increases the probability that vacant jobs are filled and thereby lowers the expected unit hiring cost. As a result, job creation becomes more attractive and firms spend more resources

¹⁴ Beauchemin and Tasci (2014) and Furlanetto and Groshenny (2016) present similar structural estimates.

Table VIII
Aggregate and Firm-Specific Moments

This table summarizes empirical and model-implied aggregate and firm-specific moments. Data on the unemployment rate are from the BLS, hiring and firing rates are from the JOLTS data set collected by the BLS, job creation and destruction rates are from Davis, Faberman, and Haltiwanger (2006), and the employment-to-unemployment transition rate is from Fujita and Nakajima (2016). Labor market tightness is the ratio of vacancies to unemployment, with vacancy data from the Conference Board and Barnichon (2010), the labor share of income is from Gomme and Rupert (2007), the relative volatility of wages to output is from Gertler and Trigari (2009), and profits and output data are from the National Income and Product Accounts. At the firm level, we compute moments of annual employment growth rates as in Davis et al. (2006) for the merged CRSP-Compustat sample. The average real market return and real risk-free rate are based on the value-weighted CRSP market return and the one-month T-bill rate, and on inflation from the BLS. The sample period is 1954 to 2014.

Moment	Data	Model
<i>Aggregate Labor Market</i>		
Unemployment rate	0.059	0.059
Hiring rate	0.035	0.035
Layoff rate	0.013	0.013
Job creation rate	0.026	0.029
Job destruction rate	0.025	0.029
Labor market tightness (LMT)	0.634	0.653
Correlation of LMT and vacancy	0.820	0.803
Correlation of LMT and unemployment rate	−0.830	−0.858
Employment-to-unemployment transition rate	0.015	0.012
Labor share of income	0.717	0.718
Volatility of aggregate wages to aggregate output	0.520	0.509
Aggregate profits to aggregate output	0.110	0.097
<i>Firm-Level Employment</i>		
Volatility of annual employment growth rates	0.239	0.240
Fraction of firms with zero annual employment growth rates	0.095	0.091
<i>Asset Prices</i>		
Average risk-free rate	0.010	0.012
Average market return	0.081	0.082

on hiring workers, thus depressing aggregate consumption. Even though labor market tightness also increases wages, it does not affect the level of aggregate consumption—it only affects its composition.¹⁵

B. Aggregate and Firm-Level Moments

Table VIII summarizes aggregate and firm-level moments computed on simulated data of the model and compares them with the data. The model closely matches firm-level and aggregate employment quantities as well as financial market moments. In equilibrium, the unemployment rate is 5.9%, the

¹⁵ Papanikolaou (2011) shows that similar intuition holds in general equilibrium for investment-specific shocks when the representative household has Epstein-Zin (1989) preferences.

aggregate hiring rate is 3.5%, and the layoff rate is 1.3% on average, which is close to what we observe in the JOLTS data set for the years 2001 to 2014.

Davis, Faberman, and Haltiwanger (2006) illustrate that the net change in employment over time can be decomposed into either worker flows, defined as the difference between hires and separations, or job flows, defined as the difference between job creation and destruction. While a single firm can either create or destroy jobs during a period, it can simultaneously have positive hires and separations. Davis, Faberman, and Haltiwanger (2006) report that the monthly job creation and job destruction rates are 2.6% and 2.5%, respectively, which our model replicates closely.

The model also performs well in replicating the dynamics of aggregate labor market tightness. Shimer (2005) estimates average labor market tightness of 0.63, while the model-implied analog is 0.65. The cyclical behavior of model-generated time series for labor market tightness, aggregate vacancies, and unemployment rate well match the correlations in the monthly data (see Table I). Changes in labor market tightness correlate positively with changes in vacancies (0.80), and negatively with changes in the unemployment rate (−0.86). Fujita and Nakajima (2016) measure separations into unemployment (EU transition rate) by computing the number of workers who switch their labor market status from employed to unemployed between month $t - 1$ and t scaled by the number of employed workers. Our model is able to closely replicate an EU transition rate of 0.015 in the data.

Given our calibration strategy, the model well matches the high labor share of income (0.72), the low relative volatility of wages to output (0.51), and the small profit margin (0.10). Data for the labor share come from Gomme and Rupert (2007) and for the volatility of aggregate wages to aggregate output from Gertler and Trigari (2009). We compute the average share of corporate profits to national income using the National Income and Product Accounts as in Gourio (2007).

At the firm level, we compute moments of annual employment growth rates as in Davis et al. (2006) for the merged CRSP-Compustat sample for the period 1980 to 2014. The model generates the observed high volatility in annual employment growth—24.0% in the model relative to 23.9% in the data. The proportional cost structure implies the existence of firms that are neither posting vacancies nor laying off workers. As emphasized by Cooper, Haltiwanger, and Willis (2007), we measure inaction as the fraction of firms with no change in employment. This quantity is 9.5% for the merged CRPS-Compustat sample. In the model, it is 9.1%, which lends support to our modeling assumption of proportional costs.

C. Equilibrium Forecasting Rules

The goal of the model is to endogenously generate a negative relation between loadings on labor market tightness and expected returns, implying a negative factor risk premium for labor market tightness, λ_t^θ . Given that aggregate productivity shocks carry a positive and efficiency shocks a negative price

of risk, $\gamma_x > 0$ and $\gamma_p < 0$, Proposition 1 (equation (27)) indicates that, for the model to generate a negative factor risk premium for labor market tightness, it is necessary that labor market tightness reacts positively to efficiency shocks, that is, $\tau_p > 0$.

The dynamics of labor market tightness (20) are the equilibrium outcome of firm policies and the solution to the labor market equilibrium condition (18). In particular, the endogenous response of labor market tightness to efficiency shocks, τ_p , depends on two economic forces, namely, a cash flow effect and a discount rate effect, which work in opposite directions. To illustrate this trade-off, we compute the Euler equation for job creation, which is given by¹⁶

$$\begin{aligned} \frac{\kappa_h}{q(\theta_t, p_t)} = \mathbb{E}_t M_{t+1} \left[e^{x_{t+1} + z_{i,t+1}} \alpha N_{i,t+1}^{\alpha-1} - w_{i,t+1} - N_{i,t+1} \frac{\partial w_{i,t+1}}{\partial N_{i,t+1}} \right. \\ \left. + (1-s) \frac{\kappa_h}{q(\theta_{t+1}, p_{t+1})} \right]. \end{aligned} \quad (31)$$

The left-hand side and the right-hand side are, respectively, the marginal cost and the marginal benefit of job creation.

In Figure 3, we illustrate this trade-off by plotting the equilibrium labor market tightness schedule as a function of matching efficiency. Consider a positive matching efficiency shock, which shifts p from p_A to p_B . A positive efficiency shock increases the rate at which vacancies are filled and thus reduces the marginal costs of hiring workers, that is, the left-hand side of the Euler equation (31). This cash flow effect implies that firms are willing to post more vacancies after a positive efficiency shock. Consequently, the labor market tightness schedule moves along the solid curve and shifts from point A to B_1 , resulting in higher labor market tightness. This effect causes a positive relation between labor market tightness and matching efficiency, that is, $\tau_p > 0$.

The cash flow effect would be the only equilibrium effect in a setting in which agents are risk-neutral. Instead, we assume that efficiency shocks carry a negative price of risk. As a result, a positive efficiency shock leads to an increase in discount rates. This discount rate effect implies that firms reduce vacancy postings, as an increase in discount rates reduces the value of job creation, that is, the right-hand side of the Euler equation (31). In Figure 3, the discount rate effect shifts the equilibrium labor market tightness schedule downward. If the discount rate channel dominates the cash flow channel (dashed dotted curve), then the new equilibrium is point B_2 , which is associated with a drop in labor market tightness and thus $\tau_p < 0$.

Our benchmark calibration implies that the cash flow effect dominates the discount rate effect (dashed curve) so that labor market tightness is positively related to matching efficiency (point B_* in Figure 3). Quantitatively, the equilibrium labor market tightness dynamics are given by

$$\log(\theta_{t+1}) = -0.0165 + 0.966 \log(\theta_t) + 0.0458 \varepsilon_{t+1}^x + 0.0682 \varepsilon_{t+1}^p. \quad (32)$$

¹⁶ For simplicity, we ignore the Lagrange multipliers on vacancy postings $V_{i,t}$ and firing $F_{i,t}$.

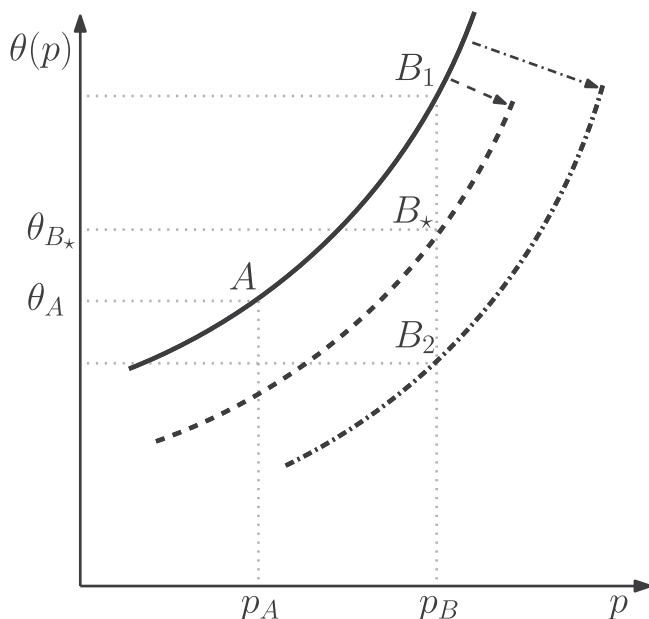


Figure 3. Labor market tightness and matching efficiency. This figure illustrates the endogenous response of equilibrium labor market tightness θ to a positive matching efficiency shock p . The solid curve corresponds to a risk-neutral economy. The dashed curve represents an economy where the cash flow effect dominates the discount rate effect in the Euler equation for job creation, while for the dashed-dotted curve the discount rate effect dominates the cash flow effect.

Labor market tightness is highly persistent and firms increase their vacancy postings after positive aggregate productivity shocks, $\tau_x > 0$, and after positive efficiency shocks, $\tau_p > 0$. Similarly, the equilibrium dynamics of (realized) market excess returns are

$$R_{t+1}^M = 0.0056 + 0.0058\varepsilon_{t+1}^x + 0.0063\varepsilon_{t+1}^p. \quad (33)$$

The average market excess return is 56 basis points per month. Market prices increase with aggregate productivity shocks, $v_x > 0$, and also with efficiency shocks, $v_p > 0$, which confirms that, on average, cash flow effects dominate the discount rate channel in determining aggregate risk premia.

These two dynamics allow us to compute stock return loadings on labor market tightness, which we use in the following section to form portfolios. Proposition 1 (equation (26)) states the functional form for labor market tightness loadings, $\beta_{i,t}^\theta$. As the above discussion highlights, efficiency shocks and not productivity shocks drive the labor market tightness premium. To illustrate the intuition behind equation (26), we assume here that loadings on the market are constant. Labor market tightness loadings are negatively correlated with expected returns when $v_x/(\tau_p v_x - \tau_x v_p) > 0$. Because productivity has a positive effect on market returns, $v_x > 0$, this condition reduces to $\tau_p/\tau_x > v_p/v_x$. Intuitively, relative to the market excess return, labor market tightness has to

Table IX
Labor Market Tightness Portfolios from the Benchmark Model

This table compares the performance of the benchmark model with the data. For the data and model, we report loadings on labor market tightness (β^θ), average value-weighted returns, and unconditional CAPM alphas and betas for each decile portfolio. Returns and alphas are expressed in percent per month.

Decile	Data				Model			
	β^θ	Return	α^{CAPM}	β^{CAPM}	β^θ	Return	α^{CAPM}	β^{CAPM}
Low	-0.80	1.14	0.02	1.25	-0.84	1.13	0.10	1.00
2	-0.38	1.10	0.11	1.03	-0.33	1.00	-0.08	1.00
3	-0.23	1.07	0.12	0.97	-0.10	0.94	-0.14	1.00
4	-0.12	1.02	0.10	0.93	0.07	0.90	-0.20	1.02
5	-0.02	1.01	0.09	0.92	0.21	0.86	-0.25	1.00
6	0.06	0.98	0.06	0.93	0.34	0.83	-0.27	1.00
7	0.16	0.99	0.05	0.96	0.45	0.80	-0.32	1.01
8	0.28	0.97	-0.02	1.04	0.56	0.77	-0.35	1.02
9	0.46	0.89	-0.18	1.17	0.70	0.73	-0.40	0.99
High	0.92	0.66	-0.52	1.35	0.88	0.68	-0.44	0.99
Low-High	-1.72	0.48	0.54	-0.10	-1.72	0.45	0.54	0.02

be more sensitive to matching efficiency shocks than to aggregate productivity shocks.

D. Cross-Section of Returns

In the previous section, we show that labor market tightness has a negative factor risk premium in equilibrium. To assess the extent to which the model can quantitatively explain the empirically observed negative relation between loadings on labor market tightness and future stock returns, we follow the empirical procedure of Section I on simulated data. In particular, we first estimate risk loadings using simulated monthly stock returns according to specification (3). Based on the estimated $\beta_{i,t}^\theta$ loadings, we next sort simulated firms into decile portfolios. Table IX compares the simulated returns with the empirical results from Table IV. As in the data, we form monthly value-weighted portfolios with annual rebalancing. The table reports average labor market tightness loadings, portfolio returns, and unconditional CAPM alphas and betas across portfolios.

The model generates a realistic dispersion in labor market tightness loadings and returns across portfolios. The average monthly return difference between the low- and high-loading portfolios is 0.45% relative to 0.48% in the data. Moreover, the CAPM cannot explain the return differences across portfolios because in the model it does not span all systematic risks. The unconditional CAPM alpha generated by the model is 0.54%, matching that in the data.

The cash flow channel of hiring costs impacts the cross-section of returns in the following way. Due to the time-variation in matching efficiency, ideally firms would like to hire after a positive matching efficiency shock when

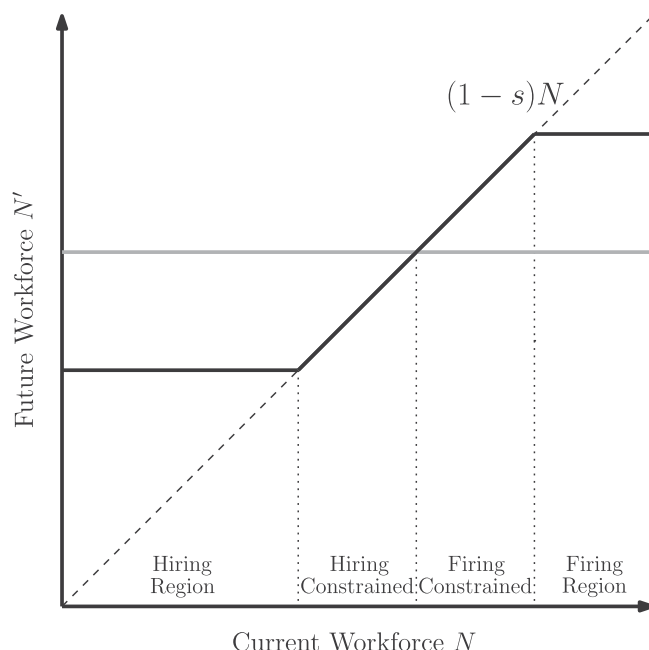


Figure 4. Optimal employment policy. This figure illustrates the optimal employment policy. The horizontal grey line is the optimal policy when adjusting the workforce is costless. The black kinked line is the optimal policy in the benchmark model under search frictions. In the middle region, where the optimal policy coincides with the dashed line $((1-s)N)$, firms are inactive. In the inactivity region below the frictionless employment target, firms have too few workers but hiring is too costly (*Hiring Constrained*). In the inactivity region above the frictionless employment target, firms have too many workers but firing is too costly (*Firing Constrained*).

marginal hiring costs, $\kappa_h/q(\theta, p)$, are low. This holds for the majority of firms, as aggregate vacancy postings increase with efficiency shocks. However, some firms are hit by low idiosyncratic productivity shocks and are optimally inactive due to proportional hiring costs.

Figure 4 illustrates the optimal firm policy. The horizontal grey line is the optimal policy when adjusting the workforce is costless. In the frictionless case, firms always adjust to the target employment size independent of the current size. The black line is the optimal policy in the benchmark model. This line has two kinks. In the middle region, where the optimal policy coincides with the dashed line $((1-s)N)$, firms are inactive. In the inactivity region below the frictionless employment target, firms have too few workers but hiring is too costly (*Hiring Constrained*). In the inactivity region above the frictionless employment target, firms have too many workers but firing is too costly (*Firing Constrained*).

For hiring-constrained firms, the discount rate channel dominates the cash flow channel, thereby depressing valuations. Their dividends are reduced not

Table X
Labor Market Tightness Portfolios from Alternative Calibrations

This table summarizes average returns of portfolios sorted by loadings on labor market tightness from alternative calibrations. In specification (1), the aggregate productivity shock is not priced, $\gamma_x = 0$. In specification (2), the matching efficiency shock is not priced, $\gamma_p = 0$. In specifications (3) and (4), the bargaining power of workers η and workers' unemployment benefit b are increased by 10% relative to the benchmark calibration, respectively. In specifications (5) to (7), the vacancy posting cost κ_h , firing cost κ_f , and fixed operating costs f are lowered by 10%, respectively.

Decile	(1) γ_x	(2) γ_p	(3) η	(4) b	(5) κ_h	(6) κ_f	(7) f
Low	1.02	0.89	1.11	1.07	1.21	1.13	1.07
2	0.94	0.90	0.92	0.96	1.09	0.99	0.94
3	0.91	0.90	0.84	0.92	1.03	0.93	0.88
4	0.89	0.91	0.82	0.88	0.99	0.88	0.84
5	0.87	0.91	0.78	0.86	0.95	0.84	0.81
6	0.86	0.92	0.75	0.83	0.92	0.81	0.78
7	0.84	0.93	0.74	0.81	0.90	0.77	0.75
8	0.83	0.94	0.72	0.78	0.88	0.74	0.72
9	0.82	0.95	0.71	0.76	0.86	0.70	0.69
High	0.80	0.98	0.69	0.73	0.84	0.68	0.65
Low-High	0.22	-0.09	0.42	0.34	0.37	0.45	0.42

only by low idiosyncratic productivity shocks but also by higher wages, which arise from tighter labor markets. Consequently, these firms have countercyclical dividends and valuations with respect to matching efficiency shocks, which renders them more risky. Since labor market tightness loadings and loadings on matching efficiency are positively related, our model can replicate the negative relation between labor market tightness loadings and expected returns. We discuss the model's mechanism more in Section IV.

E. Robustness

To gain more insights into the driving forces of the model, we consider alternative calibrations in Table X. Specifically, we are interested in the sensitivity of the return differences across β^θ -sorted portfolios to quantitative changes in key model parameters.

In specifications (1) and (2), we consider the effects of changing prices of risk of the two underlying aggregate shocks, holding the average market excess return constant. Specification (1) illustrates the impact of pricing aggregate productivity shocks by setting its price to zero, $\gamma_x = 0$. The portfolio spread is of the correct sign but of smaller magnitude compared to the data. This finding indicates the importance of modeling productivity shocks to generate cross-sectional heterogeneity among firms.

In specification (2), we assume that matching efficiency shocks are not priced, $\gamma_p = 0$. We also raise the price of risk of productivity shocks, so that the aggregate market risk premium matches the benchmark calibration. With only

productivity shocks being priced, the cross-sectional spread is small and negative at -0.09 . This experiment shows that the priced variation in aggregate matching efficiency is crucial for the labor market tightness factor to affect valuations.

Specifications (3) to (6) analyze the importance of labor search frictions by varying labor market parameters. For these exercises, we hold constant the dynamics of labor market tightness, equation (32), and study local perturbations of the parameter space. In specification (3), we increase the bargaining power of workers η by 10% to 0.127. As a result, wages become more cyclical, implying a weaker operating leverage effect. The fact that the return spread is only slightly reduced suggests that operating leverage through inelastic wages is not a key driver.

In specification (4), we increase workers' unemployment benefit b by 10% to 0.78. With greater unemployment benefits, the cyclical variation in the wage rate is reduced. Consequently, dividends of the low- β^θ portfolio are less countercyclical with respect to matching efficiency shocks and the return spread is lower.

Specifications (5) and (6) show that the costs of hiring are critical to leverage the cash flow channel and to generate the cross-sectional return spread. In particular, reducing the costs of hiring workers κ_h by 10% to 0.72 decreases the monthly return spread to 0.37%. In contrast, reducing the costs of laying off workers κ_f by 10% has little effect on the return spread.

In the baseline calibration, we set the fixed operating costs f to match the corporate profit margin in the data. In specification (7), we reduce the fixed operating costs by 10% to 0.2475. Since the steady-state ratio of hiring costs to output is very small, $\kappa_h V/N^\alpha = 0.046$, reducing operating costs makes time-varying hiring costs less relevant for firm cash flow dynamics. As a result, the return spread drops to 0.42%.

Optimal firm employment policies depend on the equilibrium dynamics of labor market tightness (32). The log-linear structure shows that, controlling for aggregate productivity, labor market tightness proxies for unobserved matching efficiency shocks. As shown in Table IX, firms' cash flow exposures to variations in labor market tightness drive the pricing of labor market tightness in the cross-section of returns. Consequently, the labor market tightness factor should also be a valid aggregate state variable, predicting future aggregate economic conditions.

Table XI confirms the ability of labor market tightness to predict future economic activity both in the data and model. In the data, we obtain quarterly time series for Gross Domestic Product, Wages and Salary Accruals, and Personal Dividend Income from the National Income and Product Accounts and total factor productivity from Fernald (2014). In the table, we report coefficients on labor market tightness growth, their t -statistics, and their adjusted- R^2 values from bivariate regressions of output growth (Panel A), wage growth (Panel B), and dividend growth (Panel C) on labor market tightness growth and total factor productivity. We run quarterly forecasting regressions for horizons up to a year.

Table XI
Forecasting Economic Activity with Labor Market Tightness

This table summarizes the ability of labor market tightness to forecast future economic activity, both in the data and in the model. The quarterly time series for output, wages, and dividends are respectively the Gross Domestic Product, Wages and Salary Accruals, and Personal Dividend Income from the National Income and Product Accounts. All series are in real terms. Total factor productivity is from Fernald (2014). We run bivariate forecasting regressions of output growth (Panel A), wage growth (Panel B), and dividend growth (Panel C) on the labor market tightness factor and growth in total factor productivity. The table reports coefficients on labor market tightness growth, their t -statistics, and their adjusted- R^2 s. Forecasting horizons range from one quarter to one year; the sample period is 1954 to 2014. In the model counterpart, we simulate 1,000 economies for 61 years and compute the average t -statistics and adjusted- R^2 s.

Horizon (quarters)	Data				Model			
	1	2	3	4	1	2	3	4
Panel A: Predicting aggregate output growth								
ϑ	0.032	0.040	0.037	0.021	0.070	0.098	0.098	0.100
t -statistic	[7.02]	[5.13]	[3.45]	[1.57]	[6.33]	[5.55]	[4.48]	[4.16]
R^2	24.55	19.94	13.51	8.26	29.19	17.05	10.46	8.44
Panel B: Predicting aggregate wage growth								
ϑ	0.043	0.062	0.077	0.075	0.092	0.115	0.108	0.103
t -statistic	[9.64]	[8.29]	[7.31]	[5.51]	[6.86]	[5.34]	[4.13]	[3.61]
R^2	37.14	34.00	30.43	23.55	33.29	16.36	8.67	6.32
Panel C: Predicting aggregate dividend growth								
ϑ	0.076	0.139	0.177	0.173	0.143	0.378	0.413	0.471
t -statistic	[3.41]	[4.50]	[4.30]	[3.40]	[2.01]	[4.16]	[3.47]	[4.42]
R^2	6.69	13.42	13.86	10.86	10.95	11.44	9.25	8.46

Labor market tightness significantly predicts output growth, wage growth, and dividend growth for horizons up to a year. This finding is consistent with our model: the changes in labor market tightness measures shocks to the matching efficiency of the labor market. Positive matching efficiency shocks predict an increase in economic activity, wages, and dividends. Although a highly procyclical aggregate variable, labor market tightness effectively captures a dimension of systematic risk absent from total factor productivity.

IV. Inspecting the Model Mechanism

In this section, we establish a strong link between the model's predictions and the data by examining the relation between loadings on labor market tightness and the cyclicalities of firms' labor decisions. We first summarize the theoretical implications of β^θ loadings and labor market tightness for firms' vacancy postings, hiring, firing, wages, and productivity. Next, using a variety of data sources, we empirically confirm these predictions.

A. Cyclicalities of Firm Labor Decisions: Model Predictions

When matching efficiency is high, most firms post vacancies, leading endogenously to high labor market tightness. Some firms, however, are hit by adverse idiosyncratic productivity shocks, and their optimal policy is not to hire even when the marginal cost of hiring is low. These firms have low dividends in periods with high matching efficiency shocks. Consequently, they have negative labor market tightness loadings and high risk exposure to labor search frictions.

The mechanism of our model thus implies that firms with low labor market tightness loadings are risky as they have countercyclical hiring policies and dividends with respect to matching efficiency shocks. When matching efficiency is high, these firms have lower vacancy rates, hiring rates, employee growth rates, wages, and productivity, and higher firing rates, than firms with high loadings. The opposite holds when matching efficiency is low. Importantly, these theoretical predictions concern the *cyclicalities* of labor characteristics, and are distinct from and complementary to predictions about the *level* of labor characteristics studied in prior literature (e.g., Belo, Lin, and Bazdresch, (2014)).

Panel A of Table XII summarizes model-simulated time-series correlations between aggregate labor market tightness and labor characteristics for portfolios formed on the basis of labor market tightness loadings. For brevity, we report the results for deciles 1 (low β^θ), 5, and 10 (high β^θ), and also show the difference between the low and high groups. We summarize the results for vacancy rates (VR), monthly, quarterly, and annual hiring rates (HR, HRQ, and HRA), firing rates (FR), employee growth rates (EGR), wages (WAGE), profitability (PROF), and labor share (LS)—detailed variable definitions are provided in Appendix A. As hypothesized, the correlations increase with labor market tightness loadings for vacancy rates, hiring rates, employee growth rates, wages, and profitability, and decrease for firing rates and labor share. For example, for firms in the low- β^θ decile, the correlation of vacancy rates with labor market tightness is -0.02 , while for the high- β^θ group this number is 0.20 . These results confirm that high- β^θ firms hire and expand when matching efficiency is high and downsize when matching efficiency is low.

The cyclicalities of firms' labor decisions is also reflected in their cash flow characteristics. The Nash bargaining wage is a function of a firm's idiosyncratic productivity and aggregate labor market tightness. Risky firms have low idiosyncratic productivity when aggregate matching efficiency is high. As a result, low- β^θ firms have less procyclical wages with respect to labor market tightness than high- β^θ firms. In addition, their profitability correlates negatively and their labor share positively with labor market tightness.

B. Cyclicalities of Firm Labor Decisions: Data and Empirical Results

We use five databases to provide empirical support for the model's economic mechanism. We obtain the first two data sets from the Bureau of Labor

Table XII

Labor Market Tightness Portfolios: Cyclical Labor Characteristics

This table reports model-simulated (Panel A) and empirical (Panel B) correlations between labor characteristics and aggregate labor market tightness for the portfolios of stocks sorted by their loadings β^θ on the labor market tightness factor, as well as for the low-high portfolio. Labor characteristics include vacancy rates (VR), monthly, quarterly, and annual hiring rates (HR, HRQ, and HRA), firing rates (FR), employee growth rates (EGR), wages (WAGE), profitability (PROF), and labor share (LS). Data in Panel B are from JOLTS, MLS, QCEW, QWI, and Compustat. Variable definitions are in Appendix . The results in Panel B are reported for two definitions of labor market tightness: the raw level as well as the residual from regressions on changes in industrial production, changes in Consumer Price Index, dividend yield, term spread, default spread, T-bill rate, and market return.

Panel A: Model									
β^θ decile	VR	HR	FR	HRA	EGR	HRQ	WAGE	PROF	LS
Low	-0.04	-0.05	0.15	-0.04	-0.08	-0.03	0.19	-0.05	0.13
Decile 5	0.13	0.12	0.07	0.09	0.05	0.14	0.21	-0.01	0.13
High	0.21	0.20	-0.09	0.16	0.15	0.20	0.23	0.05	-0.05
Low-High	-0.25	-0.26	0.24	-0.20	-0.23	-0.23	-0.04	-0.10	0.17

Panel B: Data									
β^θ decile	JOLTS		MLS	QCEW		QWI		COMPUSTAT	
	VR	HR	FR	HRA	EGR	HRQ	WAGE	PROF	LS
<i>Correlation with aggregate labor market tightness</i>									
Low	0.69	0.58	-0.16	0.30	0.48	0.38	-0.04	-0.17	0.18
Decile 5	0.71	0.69	-0.26	0.44	0.58	0.64	-0.04	-0.23	-0.40
High	0.75	0.77	-0.30	0.46	0.68	0.60	0.14	0.04	-0.28
Low-High	-0.06	-0.18	0.14	-0.15	-0.19	-0.23	-0.18	-0.22	0.46
<i>Correlation with residual aggregate labor market tightness</i>									
Low	0.16	0.05	0.09	-0.13	0.00	-0.08	0.22	0.01	0.09
Decile 5	0.41	0.19	-0.26	-0.01	0.12	0.16	0.19	0.02	-0.17
High	0.51	0.15	-0.17	0.02	0.14	0.15	0.29	0.11	-0.12
Low-High	-0.35	-0.10	0.26	-0.15	-0.14	-0.23	-0.07	-0.10	0.21

Statistics. First, we collect monthly vacancy posting and hiring rates for two-digit NAICS industries starting in December 2000 from the JOLTS. We compute the vacancy posting rate (VR) and the hiring rate (HR) as the number of vacancy postings and new hires, respectively, each scaled by the number of employees in that industry. Second, the Mass Layoff Statistics (MLS) provides monthly mass layoffs for each two-digit NAICS industry from April 1995 until May 2013.¹⁷ We use the number of mass layoff events scaled by the number of employees in that industry as a proxy for the firing rate (FR).

Our third data set comes from the Quarterly Census of Employment and Wages (QCEW), which provides monthly employment dynamics for each

¹⁷ Mass layoff statistics are adopted by Agrawal and Matsa (2013) to measure layoff propensity. The MLS program was discontinued in 2013 due to spending cuts.

six-digit NAICS industry and state starting in 1990. From QCEW, we calculate the annual employee growth rate (EGR) as the ratio of the number of employees relative to that number a year ago, as well as the annual hiring rate (HRA) as the cumulative job gains rate over the past year.

The fourth data source we use is Quarterly Workforce Indicators (QWI), which is based on the Longitudinal Employer-Household Dynamics program containing information on wage and job flows for each four-digit NAICS industry and state starting from 1993. From QWI we obtain the quarterly stable hiring rate (HRQ), computed as the number of workers who started a stable new job in the quarter scaled by the number of employees in that industry, and the average monthly wage (WAGE), which is the average monthly earnings of employees with stable jobs.¹⁸

Finally, we include relevant items related to labor from Compustat. We define profitability (PROF) as the difference between total revenue (Compustat item REVT) and cost of goods sold (COGS) scaled by book equity. Following Gorodnichenko and Weber (2016), we define labor share (LS) as total staff expenses (XLR) over net sales (SALE).

We map the data from JOLTS, MLS, QCEW, and QWI to firms in Compustat on their NAICS code and, for the latter two data sets, on headquarters state. We use the historical headquarters state from Bill McDonald's website when available, otherwise we use the headquarters state from Compustat.¹⁹ Mapping firms by industry and state is attractive as doing so links observations in QCEW and QWI to a small subset of firms. For example, the average number of firms in our sample assigned to a particular six-digit NAICS-state group is two.

Panel B of Table XII summarizes empirical time-series correlations between aggregate labor market tightness and labor characteristics for β^θ -sorted portfolios. When computing the correlations, we consider not only labor market tightness but also the residual from regressions on the changes in industrial production, the changes in the Consumer Price Index, the dividend yield, the term spread, the default spread, the T-bill rate, and the market return, similar to Table V, Panel F. We consider the second definition to account for the possibility that our results are driven by correlations of labor characteristics with these controls rather than with labor market tightness.

Using either definition, we find the same patterns as in the simulated data. The difference in the correlations of low- and high- β^θ groups is always of the hypothesized sign. In particular, correlations increase with labor market tightness loadings for vacancy rates, hiring rates, employee growth rates, wages, and profitability, and decrease for firing rates and labor share. By contrast, we do not find that the average levels of these labor characteristics display a significant pattern across portfolios, echoing our results from Tables II and VI in Section I, which further emphasizes that our model mechanism and empirical findings are complimentary to those of Belo, Lin, and Bazdresch (2014).

¹⁸ Employees with stable jobs include those who have worked with the same firm throughout the quarter.

¹⁹ The data can be found at http://www3.nd.edu/~mcdonald/10-K_Headers/10-K_Headers.html.

Taken together, the results in Table XII establish a strong relation between firm loadings on labor market tightness and the cyclicity of firm labor decisions. Firms sorted by their loadings on the labor market tightness factor differ in how their labor characteristics correlate with aggregate labor market tightness, consistent with the model predictions.

V. Conclusion

This paper studies the cross-sectional asset pricing implications of labor search frictions. The dynamic nature of the labor market implies that firms face costly employment decisions while searching for and training new employees. The ratio of vacant positions to unemployed workers, termed labor market tightness, determines the likelihood and costs of filling a vacant position.

We show that firms with low loadings on labor market tightness generate higher future returns than firms with high loadings. The return differential, at 6% per year, is economically and statistically important, cannot be explained by commonly considered factor models, and is distinct from previously studied determinants of the cross-section of equity returns.

To interpret for this result, we develop a Labor Capital Asset Pricing Model with heterogeneous firms making optimal employment decisions under labor search frictions. In the model, equilibrium labor market tightness is determined endogenously and depends on the time-varying firm-level distribution and aggregate shocks. Loadings on labor market tightness proxy for the sensitivity to aggregate shocks to the efficiency of matching workers and firms. Firms with lower labor market tightness loadings are more exposed to adverse matching efficiency shocks and hence require higher expected stock returns.

The model successfully replicates the observed return differential and empirical firm-level and aggregate labor market moments. Using micro-level data on hiring, vacancy postings, wage payment, and job creation, we show that firms sorted by their loadings on labor market tightness differ in how their labor-related characteristics correlate with aggregate labor market tightness, consistent with the model predictions. Our results suggest that labor search frictions have important implications for equity returns. Further research into the nature of interactions between labor and financial markets should provide an even more complete picture on the determinants of asset prices.

Initial submission: June 24, 2014; Accepted: September 13, 2016
Editors: Bruno Biais, Michael R. Roberts, and Kenneth J. Singleton

Appendix A: Data

We use the following definitions of CRSP-Compustat variables. ME is the natural log of the market equity of the firm, calculated as the product of its share price and number of shares outstanding. BM is the natural log of the ratio of book equity to market equity. Book equity is defined following Davis,

Fama, and French (2000) as stockholders' book equity (SEQ) plus balance sheet deferred taxes (TXDB) plus investment tax credit (ITCB) less the redemption value of preferred stock (PSTKRV). If the redemption value of preferred stock is not available, we use its liquidation value (PSTKL). If stockholders' equity value is not available in Compustat, we compute it as the sum of the book value of common equity (CEQ) and the value of preferred stock. Finally, if these items are not available, stockholders' equity is measured as the difference between total assets (AT) and total liabilities (LT). RU is the 12-month stock return run-up. HN is the hiring rate, calculated following Belo, Lin, and Bazdresch (2014) as $(N_t - N_{t-1}) / ((N_t + N_{t-1}) / 2)$, where N_t is the number of employees (EMP). AG is the asset growth rate, calculated following Cooper, Gulen, and Schill (2008) as $A_t / A_{t-1} - 1$, where A_t is the value of total assets (AT). IK is the investment rate, calculated following Belo, Lin, and Bazdresch (2014) as the ratio of capital expenditure (CAPX) divided by the lagged capital stock (PPENT). Leverage LEV is calculated as the ratio of the sum of short- and long-term debt (DLC and DLTT) to book equity. LS is the labor share, computed following Gorodnichenko and Weber (2016) as total staff expenses (XLR) divided by net sales (SALE). Profitability (PROF) is the ratio of the difference between total revenue (REVT) and cost of goods sold (COGS) scaled by book equity.

We now describe the data used to perform the calculations in Table XII. JOLTS provides the monthly vacancy posting rate (VR) and hiring rate (HR) for each two-digit NAICS industry starting from 2000/12; both rates are scaled by the number of employees in that industry. The firing rate (FR) is the monthly mass layoff rate, computed as the number of mass layoff events scaled by the number of employees in that industry. These data are obtained from MLS for each two-digit NAICS industry for 1995/04 to 2013/05. QWI provides the quarterly stable hiring rate (HRQ) and the average monthly wage (WAGE) for each four-digit NAICS industry and state starting from 1993Q1. HRQ is the number of workers who started a stable new job in the quarter scaled by the number of employees in that industry; WAGE is the average monthly earnings of employees with stable jobs. From QCEW, we compute the annual hiring rate (HRA) and employment growth rate (EGR) for each six-digit NAICS industry and state. HRA in month t is the cumulative job gains rate over the past year, given by $\sum_{i=t-11}^t \frac{N_i}{N_{t-1}} \mathbb{I}_{N_i > N_{t-1}} - 1$, where N_t is the number of employees. EGR in month t is the change in employee size compared to the same month in the previous year, that is, $\frac{N_t}{N_{t-12}} - 1$.

Appendix B: Proofs

PROOF OF PROPOSITION 1: The Euler equation shows that expected excess returns are determined by

$$-\text{Cov}_t \left(\frac{M_{t+1}}{E_t[M_{t+1}]}, R_{i,t+1}^e \right).$$

To derive a two-factor pricing representation, we follow Yogo (2006) and apply a log-linear approximation to the pricing kernel M_{t+1} such that

$$\frac{M_{t+1}}{\mathbb{E}_t[M_{t+1}]} = e^{\log(M_{t+1}) - \log(\mathbb{E}_t[M_{t+1}])} \approx 1 + m_{t+1} - \log(\mathbb{E}_t[M_{t+1}]).$$

Given this approximation, we define risk premia by

$$\mathbb{E}_t[R_{i,t+1}^e] \equiv -\text{Cov}_t(m_{t+1}, R_{i,t+1}^e). \quad (\text{B1})$$

For the pricing kernel (15), expected excess returns are given by

$$\mathbb{E}_t[R_{t+1}^e] = \gamma_x \text{Cov}_t(\varepsilon_{t+1}^x, R_{i,t+1}^e) + \gamma_p \text{Cov}_t(\varepsilon_{t+1}^p, R_{i,t+1}^e). \quad (\text{B2})$$

This equation implies that a two-factor model in ε_{t+1}^x and ε_{t+1}^p holds,

$$\mathbb{E}_t[R_{t+1}^e] = \beta_{i,t}^x \lambda^x + \beta_{i,t}^p \lambda^p, \quad (\text{B3})$$

where risk loadings are given by

$$\beta_{i,t}^x = \text{Cov}_t(\varepsilon_{t+1}^x, R_{i,t+1}^e) \quad \beta_{i,t}^p = \text{Cov}_t(\varepsilon_{t+1}^p, R_{i,t+1}^e) \quad (\text{B4})$$

and factor risk premia are

$$\lambda^x = \gamma_x \quad \lambda^p = \gamma_p. \quad (\text{B5})$$

Given the laws of motion for labor market tightness (21) and the market excess return (23), the log pricing kernel can be expressed as a function of the market excess return and log changes in labor market tightness,

$$m_{t+1} - \mathbb{E}_t[m_{t+1}] = -\gamma_M (R_{t+1}^M - \mathbb{E}_t[R_{t+1}^M]) - \gamma_\theta (\vartheta_{t+1} - \mathbb{E}_t[\vartheta_{t+1}]), \quad (\text{B6})$$

such that, based on equation (B1), expected excess returns are given by

$$\begin{aligned} \mathbb{E}_t[R_{t+1}^e] &= (\gamma_M v_x + \gamma_\theta \tau_x) \text{Cov}_t(\varepsilon_{t+1}^x, R_{i,t+1}^e) \\ &\quad + (\gamma_M v_p + \gamma_\theta \tau_p) \text{Cov}_t(\varepsilon_{t+1}^p, R_{i,t+1}^e). \end{aligned} \quad (\text{B7})$$

By matching coefficients in terms of covariances between equations (B2) and (B7), it follows that the prices of market risk γ_M and labor market tightness γ_θ solve

$$\gamma_x = \gamma_M v_x + \gamma_\theta \tau_x \quad \gamma_p = \gamma_M v_p + \gamma_\theta \tau_p,$$

implying that

$$\gamma_M = \frac{\tau_p \gamma_x - \tau_x \gamma_p}{\tau_p v_x - \tau_x v_p} \quad \gamma_\theta = \frac{v_x \gamma_p - v_p \gamma_x}{\tau_p v_x - \tau_x v_p}.$$

Since ε_{t+1}^x and ε_{t+1}^p are uncorrelated, the factor loadings β^x and β^p satisfy

$$R_{i,t+1}^e - \mathbb{E}_t[R_{i,t+1}^e] = \beta_{i,t}^x \varepsilon_{t+1}^x + \beta_{i,t}^p \varepsilon_{t+1}^p, \quad (\text{B8})$$

with loadings defined in equation (B4). Similarly, the loadings on the market return and labor market tightness satisfy

$$R_{i,t+1}^e - \mathbb{E}_t[R_{i,t+1}^e] = \beta_{i,t}^M (R_{t+1}^M - \mathbb{E}_t[R_{t+1}^M]) + \beta_{i,t}^\theta (\vartheta_{t+1} - \mathbb{E}_t[\vartheta_{t+1}]). \quad (\text{B9})$$

Notice that since R_{t+1}^M and ϑ_{t+1} are not independent, it follows that

$$\beta_{i,t}^M \neq \frac{\text{Cov}_t(R_{i,t+1}^e, R_{t+1}^M)}{\text{Var}_t(R_{t+1}^M)} \quad \beta_{i,t}^\theta \neq \frac{\text{Cov}_t(R_{i,t+1}^e, \vartheta_{t+1})}{\text{Var}_t(\vartheta_{t+1})}.$$

To compute the loadings on the market return and labor market tightness, we substitute the laws of motion (21) and (23) into the regression specification (B9) and equate it with equation (B8) to obtain

$$\beta_{i,t}^x \varepsilon_{t+1}^x + \beta_{i,t}^p \varepsilon_{t+1}^p = \beta_{i,t}^M (\nu_x \varepsilon_{t+1}^x + \nu_p \varepsilon_{t+1}^p) + \beta_{i,t}^\theta (\tau_x \varepsilon_{t+1}^x + \tau_p \varepsilon_{t+1}^p).$$

By matching the coefficients in terms of ε_{t+1}^x and ε_{t+1}^p , we obtain

$$\beta_{i,t}^x = \beta_{i,t}^M \nu_x + \beta_{i,t}^\theta \tau_x \quad \beta_{i,t}^p = \beta_{i,t}^M \nu_p + \beta_{i,t}^\theta \tau_p,$$

implying that equations (25) and (26) hold.

Next, we substitute equations (25) and (26) into equation (24), which yields

$$\mathbb{E}_t[R_{t+1}^e] = \frac{\tau_x \beta_{i,t}^p - \tau_p \beta_{i,t}^x}{\nu_p \tau_x - \nu_x \tau_p} \lambda^M + \frac{\nu_p \beta_{i,t}^x - \nu_x \beta_{i,t}^p}{\nu_p \tau_x - \nu_x \tau_p} \lambda^\theta.$$

We then match coefficients in terms of $\beta_{i,t}^x$ and $\beta_{i,t}^p$ with equation (B3), which implies

$$\begin{aligned} \lambda^x (\nu_p \tau_x - \nu_x \tau_p) &= \nu_p \lambda^\theta - \tau_p \lambda^M \\ \lambda^p (\nu_p \tau_x - \nu_x \tau_p) &= \tau_x \lambda^M - \nu_x \lambda^\theta. \end{aligned}$$

Solving for λ^θ and λ^M confirms equation (27). □

PROOF OF PROPOSITION 2: Given the dynamics for the market excess return (23), univariate loadings on the market return can be computed from

$$\begin{aligned} \beta_{i,t}^{CAPM} &= \frac{\text{Cov}_t(R_{i,t+1}^e, R_{t+1}^M)}{\text{Var}_t(R_{t+1}^M)} \\ &= \frac{\nu_x \text{Cov}_t(R_{i,t+1}^e, \varepsilon_{t+1}^x) + \nu_p \text{Cov}_t(R_{i,t+1}^e, \varepsilon_{t+1}^p)}{\text{Var}_t(R_{t+1}^M)} \\ &= \frac{\nu_x \beta_{i,t}^x + \nu_p \beta_{i,t}^p}{\nu_x^2 + \nu_p^2}. \end{aligned}$$

These loadings are consistent with conditional mispricing alphas of

$$\begin{aligned}
 \alpha_{i,t}^{CAPM} &= \mathbb{E}_t [R_{i,t+1}^e] - \beta_{i,t}^{CAPM} v_0 \\
 &= \beta_{i,t}^x \lambda^x + \beta_{i,t}^p \lambda^p - \frac{v_x \beta_{i,t}^x + v_p \beta_{i,t}^p}{v_x^2 + v_p^2} v_0 \\
 &= \left(\lambda^x - \frac{v_0 v_x}{v_x^2 + v_p^2} \right) \beta_{i,t}^x + \left(\lambda^p - \frac{v_0 v_p}{v_x^2 + v_p^2} \right) \beta_{i,t}^p. \tag{B10}
 \end{aligned}$$

Substituting conditional alphas (B10) into the CAPM pricing relation (28) implies

$$\mathbb{E}_t [R_{i,t+1}^e] = \mathbb{E}_t [R_{i,t+1}^e] - \beta_{i,t}^{CAPM} v_0 + \beta_{i,t}^{CAPM} \lambda^{CAPM},$$

which confirms that $\lambda^{CAPM} = v_0$. \square

Appendix C: Computation Details

Computation of the cross-section of stock returns is complicated because of the endogeneity of labor market tightness, which embodies the labor market equilibrium. To solve the model numerically, we discretize the state space of $\Omega = (N, z, x, p, \theta)$. All shocks (x, p, z) follow finite-state Markov chains according to Rouwenhorst (1995) with 5 states for x , 7 for p , and 11 for z . We create a log-linear grid of 500 points for current employment N in the interval $[0.01, 80]$. The lower and upper bounds of N are set such that the optimal policies are not binding in the simulation. The choice variable N' is solved for with a precision of $1e-6$. The support of labor market tightness θ is discretized into a linear grid in the interval $[0.1, 1.5]$ with 50 points. The upper and lower bounds for θ are chosen such that the simulated path of equilibrium labor market tightness never steps outside its bounds. To reduce numerical errors, we use spline interpolation whenever possible.

The computational algorithm amounts to the following iterative procedure. To save on notation, we drop the firm index i and time index t .

1. Initial guess: We make an initial guess for the coefficient vector $\tau = (\tau_0, \tau_\theta, \tau_x, \tau_p)$ of the law of motion (20). We start from $\tau = (-0.0137, 0.97, 0, 0)$ because labor market tightness tends to be highly persistent and in steady state $\tau_0 = (1 - \tau_\theta) \log(\theta^{ss}) = (1 - 0.97) \log(0.634)$.
2. Optimization: We apply value function iteration to solve the firm's optimization problem (17) given the coefficients τ of the forecasting rule. Given the discretized state space $\Omega = (N, z, x, p, \theta)$ and proportional hiring and firing costs, the firm value function solves

$$S(\Omega) = \max\{S^h(\Omega), S^f(\Omega), S^i(\Omega)\},$$

where S^h is the value of a firm that expands its workforce

$$S^h(\Omega) = \max_{N' > (1-s)N} \left\{ e^{x+z} N^\alpha - f - WN - \frac{\kappa_h}{q(\theta, p)} [N' - (1-s)N] + \mathbb{E}[M' S(\Omega') | \Omega] \right\},$$

S^f is the value of a firm that fires workers

$$S^f(\Omega) = \max_{N' < (1-s)N} \left\{ e^{x+z} N^\alpha - f - WN - \kappa_f [(1-s)N - N'] + \mathbb{E}[M' S(\Omega') | \Omega] \right\},$$

and S^i is the value of an inactive firm

$$S^i(\Omega) = e^{x+z} N^\alpha - f - WN + \mathbb{E}[M' S((1-s)N, z', x', p', \theta') | \Omega].$$

As adjustment of labor imposes a proportional cost, for a given set of shocks the firm's employment targets for the above three regimes are independent of current firm size N . This feature allows us to simplify the value function iteration.

We use spline interpolation to obtain the value function for off-grid points. We adopt a stopping criterion of $1e-6$ for the value function iteration.

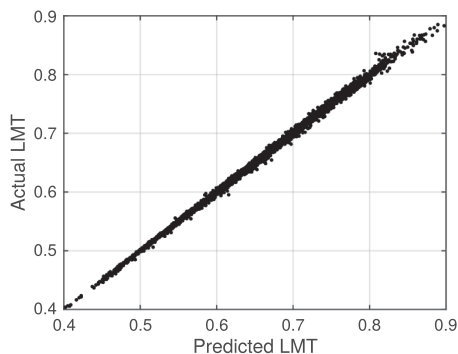
3. Nonstochastic simulation: To improve accuracy of the Krusell-Smith (1998) algorithm, we follow the so-called nonstochastic simulation approach developed by Young (2010). Using this approach, we do not have to simulate a panel with a finite number of firms, thereby avoiding Monte Carlo noise. Instead, the bivariate density over firm workforce size N and idiosyncratic productivity z is approximated with a bivariate probability mass function at each date. To obtain next period's bivariate density, the transitional laws are given by the law of motion for productivity combined with the firm's optimal policy on workforce. The bivariate probability mass function over (N, z) is sufficiently fine with dimension $n_z = 11$ and $n_N = 1,000$.

To obtain the endogenous labor market tightness, we follow Khan and Thomas (2008) and impose labor market equilibrium at each date of the simulation by solving θ as the fixed point in equation (18). Solving for equilibrium labor market tightness in each period of the nonstochastic simulation helps to reduce finite-sample noise.

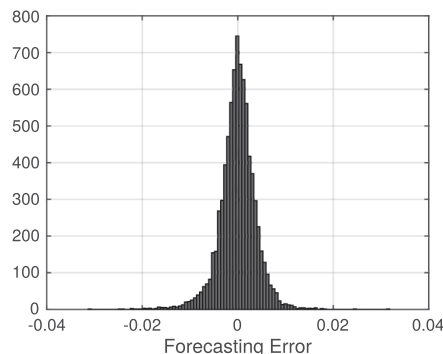
4. Update forecasting coefficients: We simulate the economy for 5,300 months and then delete the initial 300 months as burn-in. We update the coefficient vector τ by ordinary least squares. If the absolute difference between the initial guess and the updated coefficient vector is smaller than $1e-3$, the algorithm has converged; otherwise, we return to step 2.

At convergence, the fit for labor market tightness is sufficiently good with a regression R^2 higher than 0.995. The figure below shows predicted versus realized labor market tightness on simulated data as well as a histogram of the forecasting errors of log labor market tightness. Overall,

the forecasting errors of the Krusell-Smith (1998) algorithm are very small.



(a) Predicted vs. Actual Labor Market Tightness



(b) Forecasting Error

5. Stochastic simulation and portfolio sorts: We use the firm's value function and optimal employment policies to simulate a panel of 10,000 firms for 10,300 periods. Once firm values and workforce sizes are simulated, we compute monthly stock returns and labor characteristics for each firm. We estimate firm-level risk loadings similar to the empirical specification (3) and then sort firms into portfolios according to the procedure detailed in Section I.C.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.