

A Labor Capital Asset Pricing Model*

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ABSTRACT

We show that labor search frictions are an important determinant of the cross-section of equity returns. In the data, sorting firms by loadings on labor market tightness, the key statistic of search models, generates a spread in future returns of 6% annually. We propose a partial equilibrium labor market model in which heterogeneous firms make optimal employment decisions under labor search frictions. In the model, loadings on labor market tightness proxy for priced time variation in the efficiency of the matching technology. Firms with low loadings are not hedged against adverse matching efficiency shocks and require higher expected stock returns.

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I. Introduction

Dynamics in the labor market are an integral component of business cycles. More than 10 percent 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 determinant of the cross-section of equity returns.² 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 higher ratio indicates tighter labor markets so that recruiting new workers becomes more costly.

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 (cf. Shimer (2005)). To measure the sensitivity of firm value to labor market conditions, we estimate loadings of equity returns on log changes in labor market tightness controlling for the market return. We use rolling 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 1954 to 2012, we show that the loadings on changes in the labor market tightness robustly and negatively relate to future stock returns in the cross-section. Sorting stocks into deciles on the basis of the estimated loadings, we find an average return spread between firms in the low- and high-loading portfolios of 6% per year. We emphasize that this return differential is not due to

¹According to the U.S. Department of Labor, it costs one-third of a new hire's annual salary to replace them. Direct costs include advertising, sign on bonuses, headhunter fees and overtime. Indirect costs include recruitment, selection and training and decreased productivity while current employees pick up the slack.

²The importance of labor market dynamics for the business cycle has long been recognized, e.g., Merz (1995) and Andolfatto (1996).

mispricing. While it cannot be attributed to differences in loadings on commonly considered risk factors, such as those of the CAPM or the Fama and French (1993) three-factor model, it arises rationally in our theoretical 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 attributable to firm characteristics that are known to relate to future returns, we run Fama-MacBeth (1973) regressions of stock returns on lagged estimated loadings and other firm attributes. We include conventionally used control variables such as a firm's market capitalization and recently documented determinants of the cross-section of stock returns that may potentially correlate with the estimated loadings, such as hiring rates studied by Belo, Lin, and Bazdresch (2013). The Fama-MacBeth analysis confirms the robustness of results obtained in portfolio sorts. The coefficients on the labor market tightness loadings are negative and statistically significant in all regression specifications. The magnitude of the coefficients suggests that the relation is economically important: For each one standard deviation increase in the loading, subsequent annual returns decline by approximately 1.5%.

Unlike many cross-sectional predictors of equity returns that are priced within rather than across industries, labor market tightness loadings contain valuable information about future returns when considered both within and across industries. In other words, the 6% return differential we observe when allowing for industry heterogeneity across portfolios sorted on labor market tightness loadings is a convex combination of firm-specific and industry-wide components. We estimate that the firm-specific element reaches 4.0% per year whereas the industry component stands at 3.1%. Fama-MacBeth regressions confirm that labor market tightness loadings have significant predictive power for the cross-section of industry returns.

To interpret the empirical findings, we propose a labor market augmented capital asset pricing model. Building on the search framework pioneered by Diamond-Mortensen-Pissarides, we build 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.³ Under this pricing kernel, firms maximize their value either 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, it becomes less likely that vacant positions are filled, thereby increasing the expected recruiting costs to hire new workers. Since labor market tightness is a function of firms' vacancy policies, it has to be consistent with firm 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. The first shock is an aggregate productivity shock which proxies for the market return. The second shock is 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.

Both aggregate productivity and matching efficiency are not directly observable in the data. Since we would like to quantitatively compare the model with the data, we map aggregate productivity and matching efficiency into the market return and labor market tightness which are observable in the data. 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

³The canonical search and matching model is Mortensen and Pissarides (1994). More recently, firm heterogeneity in the search framework has been introduced by Cooper, Haltiwanger, and Willis (2007), Mortensen (2010), Elsby and Michaels (2013), and Fujita and Nakajima (2013).

model the *Labor Capital Asset Pricing Model*.

Quantitatively, our model replicates the negative relation between loadings on labor market tightness and future returns. Firms ideally would like to expand their workforce when the labor market is not congested, i.e., after positive shocks to the matching efficiency. These are times when the expected hiring costs are low. We assume that shocks to matching efficiency carry a negative price of risk, implying procyclical discount rates. This assumption is consistent with the general equilibrium view that positive efficiency shocks lead to lower consumption growth.

As an equilibrium outcome of the labor market, labor market tightness is positively related to matching efficiency shocks because in the model the cost channel dominates the discount rate effect. Consequently, firms with negative loadings on labor market tightness also have negative return exposure to matching efficiency shocks. Intuitively, firms that have to recruit workers after a negative matching efficiency shock have strongly countercyclical cash flows as higher recruiting costs reduce profits. As a result, these firms are riskier and require higher risk premia as their cash flows are not hedged against variation in matching efficiency.

Our paper builds on the production-based asset pricing literature started by Cochrane (1991) and Jermann (1998). Pioneered by Berk, Green, and Naik (1999), a large literature studies cross-sectional asset pricing implications of firm 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 (2012, 2013) who highlight that investment-specific shocks are related to firm risk premia. We differ by studying frictions in the labor market and specifically 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), and Kuehn, Petrosky-Nadeau, and Zhang (2012). 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 (2012) consider labor operating leverage arising from rigid wages; Donangelo (2012)

focuses on labor mobility; and Eisfeldt and Papanikolaou (2013) study organizational capital embedded in specialized labor input. We differ by exploring the impact of search costs on cross-sectional asset prices.

Closest to our paper is Belo, Lin, and Bazdresch (2013) who also emphasize that firms' hiring policies affect cross-sectional risk premia. They find that hiring growth rates predict returns in the data and explain this finding with a neoclassical Q-theory model on labor and capital adjustment costs. In contrast, we highlight the importance of search frictions in equilibrium labor markets. Recruiting workers in congested labor market is costly and firms' sensitivity to congested labor markets affects their valuation.

II. Empirical Results

In this section, we document a robust negative relation between stock return loadings on changes in labor market tightness and future equity returns. We establish this result by studying portfolios sorted by loadings on labor market tightness and confirm it using Fama-MacBeth (1973) regressions. We also show that loadings on the factor explain average industry returns.

A. Data

Our sample includes all common stocks (share code of 10 or 11) listed on NYSE, AMEX, and Nasdaq (exchange code of 1, 2, or 3) available from CRSP. To obtain meaningful risk loadings at the end of month t , we require each stock to have non-missing returns in at least 24 of the last 36 months ($t - 35$ to t). Availability of data on vacancy and unemployment rates restricts our tests to the 1954-2012 period. Fama-MacBeth regressions additionally require Compustat data on book equity and other firm attributes. Consequently, the analysis based on those data is conducted for the 1960-2012 sample. In Appendix A we list the exact formulas for all of the firm characteristics used in our tests.

B. Labor Market Tightness Factor

We obtain the monthly vacancy index from the Conference Board and the monthly labor force participation and unemployment rates from the Current Population Survey of the Bureau of Labor Statistics.⁴ We define labor market tightness as the ratio of total vacancy postings to total unemployed workers. The total number of unemployed workers is the product of the unemployment rate and the labor force participation rate (LFPR).⁵ Hence labor market tightness is given by

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

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

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

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

The time series properties of ϑ_t , its components and other macro variables are summarized in Table I. The labor market tightness factor is more volatile than any of the considered variables and has a mean that is statistically indistinguishable from zero. As expected, it is strongly correlated with its components. The factor also exhibits high correlations with default spread and changes in industrial production, which motivates us to conduct robustness tests (described below) to confirm that our empirical results are driven by changes in labor market tightness rather than by these other variables.

⁴The respective websites are <http://www.conference-board.org/data/helpwantedonline.cfm> and <http://www.bls.gov/cps>. Help Wanted Advertising Index was discontinued in October 2008 and replaced with the Conference Board Help Wanted OnLine index. We concatenate the two time series to obtain the vacancy index. The index is not available after 2009 as the Conference Board replaced it with the actual number of online advertised vacancies. Barnichon (2010) proposes the methodology to construct the index through 2012 and maintains the data on his website, <https://sites.google.com/site/regisbarnichon/research>. We use his data to extend our sample until 2012.

⁵We use the seasonally adjusted unemployment rate to reduce predictable variation in the rate.

To study the relation between stock return sensitivity to changes in labor market tightness and future equity returns, we estimate loadings $\beta_{i,\tau}^\theta$ on the ϑ factor for each stock i at the end of each month τ from rolling two-factor model regressions

$$R_{i,t} - R_{f,t} = \alpha_{i,\tau} + \beta_{i,\tau}^M(R_{M,t} - R_{f,t}) + \beta_{i,\tau}^\theta \vartheta_t + \varepsilon_{i,t}, \quad (3)$$

where $R_{i,t}$ denotes the return on stock i , $R_{f,t}$ the risk-free rate, and $R_{M,t}$ the market return in month $t \in \{\tau - 35, \tau\}$.

C. Portfolio Sorts

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

Table II presents average firm characteristics of the resulting decile portfolios. Average loadings on the labor market tightness factor range from -0.80 for the bottom decile to 0.91 for the top group. Firms in the high and low 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 factor loadings. No strong relation emerges between loadings on the labor market tightness factor and any of the other considered characteristics: book-to-market ratios, stock return runups, asset growth rates, investment rates, and hiring rates. The lack of a relation between loadings on the labor market tightness factor and hiring rates is of particular interest, as it provides the first evidence that our empirical results are distinct from those of Belo, Lin, and Bazdresch (2013).

For each decile portfolio, we obtain monthly time series of returns from January 1954 until December 2012. Table III summarizes raw returns of each decile and of the portfolio that is

long the decile with low loadings on the labor market tightness factor and short the group with high loadings. Table III also shows loadings on market, value, size, and momentum betas of each group. Firms in the high decile have somewhat larger size betas and lower momentum loadings. To control for differences in risk across the deciles, we also present unconditional alphas from market, Fama and French (1993), and Carhart (1997) models. Finally, to account for the possible time variation in betas and risk premiums, we calculate conditional alphas following either Ferson and Schadt (1996) or Boguth, Carlson, Fisher, and Simutin (2011).⁶

Both raw and risk-adjusted returns of the ten portfolios indicate a strong negative relation between loadings on the labor market tightness factor and future stock performance. Firms in the low β^θ decile earn the highest average return, 1.12% monthly, whereas the high-beta group performs most poorly, generating on average just 0.65% per month. The difference in performance of the two deciles, at 0.46%, is economically large and statistically significant (t -statistic of 3.41). The corresponding differences in both unconditional and conditional alphas are similarly striking, ranging from 0.41% (t -statistic of 2.99) for Carhart four-factor alphas to 0.52% (t -statistic of 3.83) for Fama-French 3-factor alphas.

Results of portfolio sorts thus strongly suggest that loadings on the labor market tightness factor are an important predictor of future returns. To evaluate robustness of this relation over time, Panel A of Figure 2 plots cumulative returns of the portfolio that is long the low decile and short the high group. The cumulative return is steadily increasing throughout the sample period, indicating that the relation between the loadings on the labor market tightness factor 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 factor portfolio is as volatile as the market or the momentum factors (see also Panel B of Figure 2) and achieves a Sharpe ratio (0.13) comparable to that of the

⁶More specifically, we calculate conditional alphas as intercepts from regression

$$R_{j,t} - R_{f,t} = \alpha_j + \beta_j \begin{bmatrix} 1 & Z_{t-1} \end{bmatrix}' (R_{M,t} - R_{f,t}) + e_{j,\tau}, \quad (4)$$

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. Ferson and Schadt (FS) conditional alpha is computed using as instruments demeaned dividend yield, term spread, T-bill rate, and default spread. Boguth, Carlson, Fisher, and Simutin (BCFS) 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.

market or the value factors.

We emphasize that although the difference in returns of firms with low and high loadings on the labor market tightness factor 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 the labor market tightness factor.

D. Robustness of Portfolio Sorts

We now demonstrate robustness of the relation between stock return loadings on changes in labor market tightness and future equity returns. We consider alternative portfolio formation approaches, exclude micro cap stocks, use modified definitions of the labor market tightness factor, and modify regression (3) to also include size, value, and momentum factors. Table V summarizes the results of the robustness tests.

Portfolio formation design employed in the previous section is motivated by investment strategies such as momentum studied in the prior literature. It involves holding 12 overlapping portfolios and ensures that noise due to seasonalities is reduced. We consider two alternatives: forming portfolios only once a year and holding the portfolios for one month. 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 future performance of low and high β^θ deciles. For example, the difference in average returns of the low and high groups reaches 0.55% monthly when portfolios are formed once a year, compared to 0.46% reported in Table III.

We next explore the sensitivity of the results to the length of time between calculation of β^θ and beginning of the holding period. Our base-case results in Table III 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. The assumption is well-justified in the current markets, where the data for any month are

typically available within days after the end of that month. To allow for a 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 the methodology. The difference in future returns of stocks with low and high loadings on the labor market tightness factor reaches 0.47% per month.

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

Panel E of Table V shows that the results are also robust to excluding microcaps, which we define as stocks with market equity below the 20th NYSE percentile. Microcaps on average represent just 3% of the total market capitalization of all stocks listed on NYSE, Amex, and Nasdaq, but they account for about 60% of the total number of stocks. Excluding these stocks from the sample does not meaningfully impact the results.⁷

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 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 re-defining the labor market tightness factor as the residual $\tilde{\vartheta}_t$ from a time-series regression

$$\vartheta_t = \gamma_0 + \gamma_1 IP_t + \gamma_2 CPI_t + \gamma_3 DY_t + \gamma_4 TB_t + \gamma_5 TS_t + \gamma_6 DS_t + \tilde{\vartheta}_t, \quad (5)$$

where IP_t , CPI_t , DY_t , TB_t , TS_t , and DS_t are changes in industrial production, changes in the consumer price index, the dividend yield, the T-bill rate, the term spread, and the default spread, respectively. Our second alternative definition calls for computing the labor market tightness factor as the residual from fitting the log of labor market tightness to an ARMA(1,1)

⁷Untabulated results also confirm robustness to imposing a minimum price filter and to excluding Nasdaq-listed stocks.

model. The disadvantage of both of these approaches is that they introduce a look-ahead bias as the entire sample is used to estimate the labor market tightness factor. Yet, the first alternative definition allow us to focus on the component of labor market tightness that is unrelated to other macro variables that might have non-zero prices of risk. And 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 the changes in the definition of the labor market tightness factor. The difference in future raw and risk-adjusted returns of portfolios with low and high loadings on the factor are always statistically significant and economically important, ranging between 0.41% and 0.51% monthly.

In Table III, we compute alphas from multi-factor models to ensure that the relation between loadings on the labor market factor 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 are not sensitive to this alternative method of estimating β^θ .

Finally, we also evaluate the relation between loadings β^θ on the labor market tightness factor and future equity returns conditional on stocks' market betas β^M . We sort firms into quintiles based on their β^θ and β^M loadings and study subsequent returns of each of the resulting 25 portfolios. Table ?? of the Appendix shows that irrespective of whether we consider independent sorts or dependent sorts (e.g., first on β^M and then by β^θ within each market beta quintile), stocks with low loadings on the labor market tightness factor significantly outperform stocks with high loadings.

E. Fama-MacBeth Regressions

The empirical evidence from portfolio sorts provides a strong indication of a negative relation between the stock return loadings on changes in labor market tightness, β^θ , and subsequent equity returns. However, such univariate analysis does not account for other firm characteristics that have been shown to relate to future returns. We compare the loadings on the labor market tightness factor to 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 characteristics. To this end, we run annual Fama-MacBeth (1973) regressions

$$R_{i,T} = \gamma_T^0 + \gamma_T^1 \beta_{i,\tau}^\theta + \sum_{j=1}^K \gamma_T^j X_{i,T}^j + \eta_{i,T}, \quad (6)$$

where $R_{i,T}$ is stock i return from July of year T to June of year $T + 1$, $\beta_{i,\tau}^\theta$ is the loading from regressions (3) with τ corresponding to May of year T , and $X_{i,T}$ are K control variables all measured prior to the end of June of year T . The timing of the variable measurement in the regression follows the widely accepted convention as in Fama and French (1992).

We include in the Fama-MacBeth regressions commonly considered control variables such as a firm’s market capitalization (ME), book-to-market ratio (BM) and return runup (RU) (Fama and French (1992); Jegadeesh and Titman (1993)). We also consider other recently documented determinants of the cross-section of stock returns, including the asset growth rate (AG) of Cooper, Gulen, and Schill (2008) as well as the labor hiring (HN) and investment rates (IK) of Belo, Lin, and Bazdresch (2013). We winsorize all independent variables cross-sectionally at 1% and 99%.

Table VI summarizes the results of the Fama-MacBeth 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 approximately 1.5%. Average loadings of firms in the bottom and top decile portfolios are 3.5 standard deviations apart, suggesting that the difference in future stock returns of the two groups exceeds 5% per year, in line with the results presented in Table III.

The labor market tightness factor is highly correlated with its components and with changes in industrial production (see Table I). To ensure that our results are not driven by either of these macro variables, we first estimate loadings β^{LFPR} , β^{Unemp} , β^{Vac} , and β^{IP} from a two-factor regression of stock excess returns on market excess returns and log changes in either labor force participation rate, unemployment rate, vacancy index, or industrial production, respectively. These loadings are estimated in the same manner as is β^θ in equation (3). We next run Fama-MacBeth regressions of annual stock returns on lagged loadings β^{LFPR} , β^{Unemp} , β^{Vac} , and β^{IP} and on other control variables. Table ?? of the Appendix shows 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 the labor market tightness or by changes in industrial production.

F. Industry-Level Analysis

The ability of commonly considered firm characteristics to predict stock returns is known to be stronger when these characteristics are computed relative to industry averages. In other words, many determinants of the cross-section of stock returns are priced within rather than across industries (e.g., Cohen and Polk (1998), Asness, Burt, Ross, and Stevens (2000), Simutin (2010), Novy-Marx (2011)). We now show that unlike many other cross-sectional predictors of stock returns, β^θ contains better information about future returns when considered *across* rather than *within* industries. Our goal in this section is to understand how much of the negative relation between β^θ and future stock returns is due to industry-specific vs firm-specific (non-industry) components.

We begin our analysis by modifying the portfolio assignment methodology used above to ensure that all β^θ decile portfolios have similar industry characteristics. To achieve this, we sort firms into deciles within each of the 48 industries as defined by Ken French and then aggregate firms across industries to obtain ten industry-neutral portfolios. Panel A of Table VII shows that the differences in future performance of firms with low and high loadings on the labor market tightness factor are slightly muted relative to those in Table III. For example, the return of the Low-High portfolio reaches 0.36% monthly when portfolio assignment is done within industries whereas the corresponding figure is 0.46% when industry composition is allowed to vary across deciles.

Larger difference in future performance of low and high β^θ stocks when we allow for industry heterogeneity across decile portfolios is particularly interesting given that many known premiums are largely intra-industry phenomena. This result suggests that the labor market tightness factor may be priced in the cross-section of industry portfolios. To investigate this conjecture, we assign 48 value-weighted industry portfolios into deciles on the basis of

their loadings on the labor market tightness factor and study future returns of the resulting decile portfolios. Panel B of Table VII shows that industries with low loadings outperform industries with high loadings by between 0.35% per month.⁸

III. Model

The goal of this section is to provide an economic model which 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 assume that the only input to production is labor. We thus abstract from capital accumulation and investment frictions. Firms generate revenue, $Y_{i,t}$, according to a decreasing returns to scale production function

$$Y_{i,t} = e^{x_t + z_{i,t}} N_{i,t}^\alpha, \quad (7)$$

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

$$x_t = \rho_x x_{t-1} + \sigma_x \varepsilon_t^x, \quad (8)$$

$$z_{i,t} = \rho_z z_{i,t-1} + \sigma_z \varepsilon_{i,t}^z, \quad (9)$$

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

The dynamics of firms' workforce are determined in a Kydland-Prescott time-to-build fashion. Firms can expand the workforce by posting vacancies, $V_{i,t}$, to attract unemployed workers. The key friction of search markets is that not all the posted vacancies are filled in a

⁸Industry portfolios are from Ken French's data library. Table ?? of the Appendix provides summary statistics for the industry portfolios.

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. Once workers and firms are randomly matched, a constant fraction s of workers quit voluntarily and $F_{i,t}$ of them are laid off by the firm. Taken together, this implies the following law of motion for the firm workforce size

$$N_{i,t+1} = (1 - s)N_{i,t} + q(\theta_t, p_t)V_{i,t} - F_{i,t}. \quad (10)$$

The matching efficiency shock p_t follows an AR(1) process with autocorrelation ρ_p and i.i.d. normal innovation ε_t^p which is uncorrelated with aggregate productivity innovations ε_t^x

$$p_t = \rho_p p_{t-1} + \sigma_p \varepsilon_t^p. \quad (11)$$

This matching efficiency shock is common across firms and thus represents aggregate risk. This shock was first studied by Andolfatto (1996) who argued that it can be interpreted as a reallocative shock, 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 different channels that can explain changes in matching efficiency. Using micro-data Barnichon and Figura (2011) show that fluctuations in matching efficiency can be related to the composition of the unemployment pool, such as a rise in the share of long-term unemployed or fluctuations in participation due to demographic factors, and dispersion in labor market conditions; Herz and van Rens (2011) and Sahin, Song, Topa, and Violante (2012) highlight the role of skill and occupational mismatch between jobs and workers; Sterk (2010) 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, θ_t , determines how easily vacant jobs can be filled. It is measured as the ratio of aggregate vacancies, \bar{V}_t , to the aggregate unemployment level, \bar{U}_t , i.e., $\theta_t = \bar{V}_t/\bar{U}_t$. The aggregate number of vacancies is simply the sum of all firm-level vacancies

$$\bar{V}_t = \int V_{i,t} d\mu_t, \quad (12)$$

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 is defined as the sum of employed and unemployed with mass one. Thus, the total number of unemployed equals

$$\bar{U}_t = 1 - \int N_{i,t} d\mu_t. \quad (13)$$

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

$$\mathcal{M}(\bar{U}_t, \bar{V}_t, p_t) = \frac{e^{p_t} \bar{U}_t \bar{V}_t}{(\bar{U}_t^\xi + \bar{V}_t^\xi)^{1/\xi}}, \quad (14)$$

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

$$q(\theta_t, p_t) = \frac{\mathcal{M}(\bar{U}_t, \bar{V}_t, p_t)}{\bar{V}_t} = e^{p_t} \left(1 + \theta_t^\xi\right)^{-1/\xi}. \quad (15)$$

The matching rate is decreasing in θ , meaning that an increase in the relative scarcity of unemployed workers relative to job vacancies makes it more difficult for a firm to fill a vacancy, and increasing in p , as a positive efficiency shock makes finding a worker easier.

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 each firm and its workforce according to a Nash bargaining wage rate. Following Stole and Zwiebel (1996), we derive the Nash bargaining wage in multi-worker firms with decreasing returns to scale production technology. Specifically, firms renegotiate wages every period with its 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 represent the value of their outside option. They are also rewarded the saving of hiring costs that firms enjoy when a job position is filled, $\kappa_h \theta_t$, where κ_h is the unit cost of vacancy posting. As a result, wages are given by

$$w_{i,t} = \eta \left[\frac{\alpha}{1 - \eta(1 - \alpha)} \frac{Y_{i,t}}{N_{i,t}} + \kappa_h \theta_t \right] + (1 - \eta)b. \quad (16)$$

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 all the existing 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 the firm when labor market are tighter. Unemployment benefits provide a floor to wages.

D. Firm Value

We do not model the supply side of labor coming from households. This would require to solve 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 efficiency shock p_t are priced. The log of the pricing kernel is given by

$$\ln M_{t+1} = \ln \beta - \gamma_x (\sigma_x \varepsilon_{t+1}^x + \phi x_t) - \gamma_{p,t} (\sigma_p \varepsilon_{t+1}^p + \phi p_t) \quad (17)$$

where β is the time discount rate, γ_x the constant price of aggregate productivity shocks, $\gamma_{p,t} = \gamma_{p,0} e^{\gamma_{p,1} p_t}$ the time-varying price of efficiency shocks, and ϕ measures the sensitivity of interest rates.

The objective of the firm is to maximize its value $S_{i,t}$ either by posting vacancies $V_{i,t}$ to hire workers or by firing $F_{i,t}$ employed workers to downsize. Both adjustments are costly at a rate κ_h for hiring and κ_f for firing. Firms also pay fixed f_0 and proportional f_1 operating costs. Dividends to shareholders are given by revenues net of operating, hiring, and firing costs as well as wage payments

$$D_{i,t} = Y_{i,t} - f_0 - f_1 N_t - w_{i,t} N_{i,t} - \kappa_h V_{i,t} - \kappa_f F_{i,t}. \quad (18)$$

The firm's Bellman equation solves

$$S_{i,t} = \max_{V_{i,t} \geq 0, F_{i,t} \geq 0} \{D_{i,t} + \mathbb{E}_t[M_{t+1}S_{i,t+1}]\}, \quad (19)$$

subject to equations (7)–(17). Notice that the firm's problem is well-defined given labor market tightness θ_t and an expectation about how it evolves. Given optimal (cum-dividend) firm value $S_{i,t}$, expected stock returns are

$$\mathbb{E}_t[R_{i,t+1}] = \frac{S_{i,t+1}}{S_{i,t} - D_{i,t}}. \quad (20)$$

E. Equilibrium

Optimal firm employment policies depend on the dynamics of the labor market equilibrium. More specifically, the probability q , of a vacancy being filled with a worker, is a function of aggregate labor market tightness θ and matching efficiency p . Each individual firm is atomistic and takes labor market tightness as exogenous.

Let $\Omega_{i,t} = (N_{i,t}, z_{i,t}, x_t, p_t, \mu_t)$ be the vector of state variables and Γ be the law of motion for the time-varying firm distribution μ_t ,

$$\mu_{t+1} = \Gamma(\mu_t, x_{t+1}, x_t, p_{t+1}, p_t). \quad (21)$$

A given distribution μ_t of the firm-level state space together with the aggregate shocks implies a value for labor market tightness θ_t . Hence, equilibrium in the labor market requires that labor market tightness θ_t at each date is determined as a fixed point satisfying

$$\theta_t = \frac{\int V(\Omega_{i,t}) d\mu_t}{L - \int N_{i,t} d\mu_t}. \quad (22)$$

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 $S(\Omega_{i,t})$, (iii) a law of motion of firm distribution Γ , such that: Optimality: Given the pricing kernel (17), Nash bargaining wage rate (16), and labor market tightness θ_t , $V(\Omega_{i,t})$ and $F(\Omega_{i,t})$ solve the firm's Bellman equation (19) where $S(\Omega_{i,t})$ is its solution; Consistency: θ_t is consistent with the labor market equilibrium (22), and the law of motion of firm distribution Γ 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 distribution. Rather than solving for the high dimensional firm distribution μ_t exactly, we follow Krusell and Smith (1998) and approximate the firm-level distribution with one moment. In search models, labor market tightness θ_t is a sufficient statistic to solve the firm's problem (19) and thus enters the state vector replacing μ_t , i.e., $\Omega_{i,t} = (N_{i,t}, z_{i,t}, x_t, p_t, \theta_t)$.

To approximate the law of motion Γ in equation (21), we assume a log-linear functional form

$$\log \theta_{t+1} = \tau_0 + \tau_\theta \log \theta_t + \tau_x(x_{t+1} - \rho_x x_t) + \tau_p(p_{t+1} - \rho_p p_t). \quad (23)$$

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 change in logs of labor market tightness

$$\vartheta_{t+1} = \tau_0 + (\tau_\theta - 1) \log \theta_t + \tau_x(x_{t+1} - \rho_x x_t) + \tau_p(p_{t+1} - \rho_p p_t). \quad (24)$$

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

Our application of Krusell and Smith (1998) differs from Zhang (2005) along two dimensions. First, we model future labor market tightness, θ_{t+1} , as a function of the firm distribution at time $t + 1$; hence, it is not in the information set of date t . The forecasting rule (23) 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 states. 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 (22). Hence, there is no discrepancy between the forecasted θ_{t+1} and the realized θ_{t+1} .

G. Equilibrium Risk Premia

The model is driven by two aggregate shocks: aggregate productivity and matching efficiency. To test the model's cross-sectional return implications on data, it is advantageous to derive an approximate linear pricing model. Based on the Euler equation for expected excess returns, we can apply a log-linear approximation to the pricing kernel (17) implying

$$\mathbb{E}_t[R_{i,t+1}^e] \approx \beta_{i,t}^x \lambda^x + \beta_{i,t}^p \lambda_t^p \quad (25)$$

where $\beta_{i,t}^x$ 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.⁹

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 approximate the return on the market as an affine function of the aggregate shocks

$$R_{M,t+1}^e = \nu_0 + \nu_x(x_{t+1} - \rho_x x_t) + \nu_p(p_{t+1} - \rho_p p_t). \quad (26)$$

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

Proposition 1 *Given a log-linear approximation to the pricing kernel (17) and laws of motion (24) and (26), the log pricing kernel satisfies*

$$m_{t+1} = -\gamma_{M,t} R_{M,t+1}^e - \gamma_{\theta,t} \vartheta_{t+1}, \quad (27)$$

where the prices of market risk γ_M and labor market tightness γ_θ are given by

$$\gamma_{M,t} = \frac{\tau_p \gamma_x - \tau_x \gamma_{p,t}}{\tau_p \nu_x - \tau_x \nu_p} \quad \gamma_{\theta,t} = \frac{\nu_x \gamma_{p,t} - \nu_p \gamma_x}{\tau_p \nu_x - \tau_x \nu_p}. \quad (28)$$

The pricing kernel (27) implies a linear pricing model in the form of

$$\mathbb{E}_t[R_{i,t+1}^e] = \beta_{i,t}^M \lambda_t^M + \beta_{i,t}^\theta \lambda_t^\theta, \quad (29)$$

⁹All proofs of this section can be found in Appendix C.

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

$$\beta_{i,t}^M = \frac{\tau_p}{\tau_p \nu_x - \tau_x \nu_p} \beta_{i,t}^x + \frac{-\tau_x}{\tau_p \nu_x - \tau_x \nu_p} \beta_{i,t}^p \quad (30)$$

$$\beta_{i,t}^\theta = \frac{-\nu_p}{\tau_p \nu_x - \tau_x \nu_p} \beta_{i,t}^x + \frac{\nu_x}{\tau_p \nu_x - \tau_x \nu_p} \beta_{i,t}^p \quad (31)$$

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

$$\lambda_t^M = \nu_x \lambda^x + \nu_p \lambda_t^p \quad \lambda_t^\theta = \tau_x \lambda^x + \tau_p \lambda_t^p. \quad (32)$$

We call relation (29) the *Labor Capital Asset Pricing Model*.¹⁰ The goal of the model is to endogenously generate a negative factor risk premium of labor market tightness, λ_t^θ . We will explain the intuition behind Proposition 1 after the calibration in Section IV.B.

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 mis-specified one-factor CAPM and compare the CAPM implied alphas with the data. The following proposition summarizes this idea.

Proposition 2 *Given a log-linear approximation to the pricing kernel (17) and laws of motion (24) and (26), the CAPM implies a linear pricing model in the form of*

$$\mathbb{E}_t[R_{i,t+1}^e] = \alpha_{i,t}^{CAPM} + \beta_{i,t}^{CAPM} \lambda_t^{CAPM}, \quad (33)$$

where the CAPM mispricing alphas are given by

$$\alpha_{i,t}^{CAPM} = \beta_{i,t}^\theta \gamma_{\theta,t} \frac{(\tau_x \nu_p - \nu_x \tau_p)^2 \sigma_p^2 \sigma_x^2}{\nu_x^2 \sigma_x^2 + \nu_p^2 \sigma_p^2}, \quad (34)$$

CAPM loadings on the market return by

$$\beta_{i,t}^{CAPM} = \frac{\nu_x \sigma_x^2}{\nu_x^2 \sigma_x^2 + \nu_p^2 \sigma_p^2} \beta_x + \frac{\nu_p \sigma_p^2}{\nu_x^2 \sigma_x^2 + \nu_p^2 \sigma_p^2} \beta_p, \quad (35)$$

and the CAPM factor risk premium $\lambda_t^{CAPM} = \lambda_t^M = \nu_x \lambda^x + \nu_p \lambda_t^p$.

¹⁰Note, that the risk loadings (30) and (31) are not univariate regression betas because the market return and labor market tightness are correlated.

IV. Quantitative Results

In this section, we describe our calibration procedure and the benchmark parameterization. We first present the numerical results of the equilibrium forecasting rules. Given the equilibrium dynamics for the labor market, we calculate theoretical loadings on labor market tightness and show that the model is consistent with the inverse relation between loadings and expected future stock returns in the cross-section. At the end of this section, we discuss the main mechanism driving our model.

We solve the competitive equilibrium numerically in the discretized state space $\Omega_{i,t}$ using an iterative algorithm described in Appendix D. Given the equilibrium forecasting rule, firms make optimal employment decisions. We simulate a panel of 5,000 firms for 5,000 periods.

A. Calibration

This section describes how we calibrate the parameter values. We adopt a monthly frequency because labor market and equity market data are available at that frequency. Table VIII summarizes the parameter calibration of the benchmark model.

The labor literature provides several empirical studies to calibrate the labor market parameters. According to Davis, Faberman, and Haltiwanger (2006) and Davis, Faberman, Haltiwanger, and Rucker (2010), the monthly total separation rate measured in the Job Openings and Labor Turnover Survey (JOLTS) by the BLS is around 4%. The total separation rates captures both voluntary quits and involuntary layoffs. As firms in our model can optimize over the number of worker to be laid off, we calibrate the separation rate only to the voluntary quit rate which captures workers switching jobs, for instance, for reasons of career development, better pay or preferable working conditions. We set the monthly exogenous quit rate s at 2.2% so that the model is consistent in steady state with the hiring and layoff rate reported by JOLTS.

The elasticity of the matching function determines how quickly the vacancy filling rate falls as a function of labor market tightness. Based on the structural estimate in den Haan, Ramey, and Watson (2000), we set the elasticity ξ at 1.27. This number is also in line with Shimer

(2005) who finds that the aggregate monthly job finding rate f equals 0.45 and the average vacancy filling rate $q = 0.71$. In steady state, labor market tightness equals $f/q = 0.634$ and the vacancy filling rate is given by $q = ((f/q)^\xi + 1)^{-1/\xi}$ which implies $\xi = 1.28$.

The bargaining power of workers η determines the rigidity of wages over the business cycle. As emphasized in Hagedorn and Manovskii (2008), the elasticity of aggregate wages with respect to labor productivity is only 0.45 in the data, meaning, that wages are half as volatile as labor productivity. Similarly, Gertler and Trigari (2009) find that the relative volatility of wages to output is 0.52 in the data. We follow their calibration strategy and set η at 0.10 to match the relative volatility of wages to output.¹¹ 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 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 $b = 0.4$. Hagedorn and Manovskii (2008), on the other hand, 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 at 0.75.¹²

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 as well as the labor elasticity of output α . Since the value of unemployment activities is close to the labor share of income, we can easily match the labor share by setting the labor elasticity of output α at 0.75. We assume less curvature in the production function than, for instance, Cooper, Haltiwanger, and Willis (2007). They, however, do not model wages as the outcome of Nash bargaining.

¹¹Hagedorn and Manovskii (2008) set the bargaining power of workers at 0.054 and Lubik (2009) estimates it to be 0.03.

¹²Similarly, Lubik (2009) estimates that unemployment activities amount to 0.74 relative to unit mean labor productivity.

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 estimates of hiring costs are sparse, we set κ_h at 0.4 to match the aggregate hiring rate of workers. 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 legislations are a set of rules and restrictions governing the dismissals of employees. Such provisions impose a firing cost to the firm that has two separate dimensions: a transfer from the firm to the worker to be 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 for the magnitude of this parameter, we set the flow costs of firing workers κ_f to match the aggregate layoff rate.

Without fixed operating costs, the model would overstate the net profit margin of firms. Similarly, without proportional operating costs, the model implied aggregate unemployment would be unrealistically small. Consequently, we target the aggregate profit to aggregate output ratio and the unemployment rate to calibrate fixed f_0 and proportional f_1 operating costs.

We calibrate the two aggregate shocks following the macroeconomics literature. Since labor is the only input to production, the 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 $\sigma_x = 0.005$. 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 quarterly frequency. We follow more recent estimates by Cheremukhin and Restrepo-Echavarria (2010) and set $\rho_p = 0.88^{1/3}$ and $\sigma_p = 0.025$.¹³

For the persistence ρ_z and conditional volatility σ_z of firm-specific productivity, we choose values close to those used by Zhang (2005), Gomes and Schmid (2010), and Fujita and Nakajima (2013) to match the cross-sectional properties of firm hiring policies.

¹³Similar structural estimates are contained in Furlanetto and Groshenny (2012) and Beauchemin and Tasci (2012).

The pricing kernel is calibrated to match financial moments. We choose the time discount rate β and the pricing kernel parameters $\gamma_x, \gamma_{p,0}, \gamma_{p,1}, \phi$ so that the model approximately matches the first and second moments of the risk-free rate and market return. This requires that β equals 0.9935, $\gamma_x = 1$, $\gamma_{p,0} = -5$, $\gamma_{p,1} = 5$, and $\phi = -0.0225$. Importantly, shocks to matching efficiency carry a negative price of risk and are pro-cyclical. A small parameter value of ϕ allows for a time-varying but smooth interest rate.

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 function 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 on hiring workers, thus depressing aggregate consumption.¹⁴

Table IX summarizes aggregate moments computed on simulated data of the model. The data for the unemployment rate are from the BLS, the hiring and layoff rates are from the JOLTS dataset collected by the BLS, the labor share of income is from Gomme and Rupert (2007), the volatility of aggregate wages to aggregate output is from Gertler and Trigari (2009). At the firm level, we compute annual employment growth rate, its volatility and skewness as in Davis, Haltiwanger, Jarmin, and Miranda (2006) for the merged CRSP-Compustat sample for the period 1980-2012. Similarly, we determine the fraction of firms with no change in employment as emphasized by Cooper, Haltiwanger, and Willis (2007). We obtain the monthly series of the value-weighted market return and one-month Treasury bill from CRSP, and inflation from the Federal Reserve to compute the annualized first and second moments of the one-month real risk-free rate and real market return.

Overall, the model closely matches firm-level and aggregate employment quantities as well as financial market moments. In equilibrium, the aggregate unemployment rate is 5.8%, the monthly aggregate hiring rate is 3.5%, and the layoff rate is 1.3%, close to what we observe in the data. The model is also in with the average level of labor market tightness and its

¹⁴The same intuition is shown to hold in general equilibrium for investment-specific shocks by Papanikolaou (2011).

volatility. The labor share of income is 71% and the volatility of wages to output is 52%, close to empirical estimates.

At the firm level, the model generates the observed high volatility in annual employment growth, 21.9% in the model relative to 21.6% in the data. Moreover, this volatility is coming from hiring and not firing, since the excess skewness of annual employment growth is positive and around 0.12 in both data and model. The proportional cost structure implies the existence of firms that are neither posting vacancies nor laying off workers. The percentage of CRSP-Compustat firms with zero net annual employment growth rate is about 9.7%. In the model, this fraction is 7.7%. This finding lends support for the standard modeling assumption of proportional costs.

The pricing kernel and its calibration give rise to a realistic annual average market return (8.8%) and volatility (17.4%). In addition, the average risk-free rate is low (1%) and smooth (2%) as in the data.

B. Equilibrium Forecasting Rules

The goal of the model and calibration is to endogenously generate a negative relation between loadings on labor market tightness and expected returns, implying a negative factor risk premium of 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 $\gamma_{p,0} < 0$, Proposition 1 (Equation (32)) states that the model only generates a negative factor risk premium of labor market tightness if labor market tightness reacts positively to efficiency shocks, i.e., $\tau_p > 0$.

The dynamics of labor market tightness (23) are the equilibrium outcome of firm policies and the solution to the labor market equilibrium condition (22). In particular, the endogenous response of labor market tightness to efficiency shocks, $\tau_p > 0$, depends on two economic forces, namely, a cash-flow and a discount rate effects, which work in opposite directions. To illustrate this trade-off, we compute the Euler equation for job creation, which is given by¹⁵

$$\frac{\kappa_h}{q(\theta_t, p_t)} = \mathbb{E}_t M_{t+1} \left[e^{x_{t+1} + z_{i,t+1}} \alpha N_{i,t+1}^{\alpha-1} - w_{i,t+1} - N_{i,t+1} \frac{\partial w_{i,t+1}}{\partial N_{i,t+1}} + (1-s) \frac{\kappa_h}{q(\theta_{t+1}, p_{t+1})} \right]. \quad (36)$$

¹⁵For simplicity, we ignore the Lagrange multipliers on vacancy postings $V_{i,t}$ and firing $F_{i,t}$.

The left-hand side is the marginal cost and the right-hand the marginal benefit of job creation.

In Figure 3, we illustrate this trade-off by plotting labor market tightness as a function of matching efficiency. Consider a positive matching efficiency shock which shifts p_0 to p_1 . A positive efficiency shock increases the rate at which vacancies are filled and thus reduces the marginal costs of hiring workers, i.e., the left-hand side of the Euler equation (36). This cash-flow effect implies that firms are willing to post more vacancies after a positive efficiency shock. Consequently, the equilibrium moves along the solid black line and shifts from point A to B, resulting in a higher labor market tightness θ_1 . This effect causes a positive relation between labor market tightness and matching efficiency, i.e., $\tau_p > 0$.

The cash-flow effect would be the only equilibrium effect in a setting in which agents are risk-neutral. Since we are interested in the pricing of labor market risks, 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, i.e., the right-hand side of the Euler equation (36). 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 (blue dotted line), then the new equilibrium is point D, which is associated with a drop in labor market tightness to θ_3 and thus $\tau_p < 0$.

In line with the equity market data, our benchmark calibration implies that the cash-flow effect dominates the discount rate effect (dashed red line) such that labor market tightness is positively related with matching efficiency (point C in Figure 3). Quantitatively, the equilibrium labor market tightness dynamics are

$$\log \theta_{t+1} = 0.0043 + 0.9725 \log \theta_t + 5.6190(x_{t+1} - \rho_x x_t) + 0.1744(p_{t+1} - \rho_p p_t).$$

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 return are

$$R_{M,t+1}^e = 0.0080 + 0.8618(x_{t+1} - \rho_x x_t) - 2.1741(p_{t+1} - \rho_p p_t).$$

The average market excess return is 88 basis points per month and market prices increase after aggregate productivity shocks, $\nu_x > 0$, and decrease after efficiency shocks, $\nu_p < 0$, which is consistent with a positive price of risk for productivity shocks and a negative one for efficiency shocks.

These two dynamics allow us to compute stock return loadings on labor market tightness, which we will use in the following section to form portfolios. Proposition 1 (Equation (31)) states the functional form for labor market tightness loadings, $\beta_{i,t}^\theta$. As the above discussion highlights, efficiency shocks and not productivity shocks are the driver of the labor market tightness premium. So to gain intuition behind Equation (31), we assume that loadings on the market are constant for simplicity. Labor market tightness loadings are negatively correlated with expected returns when $\nu_x/(\tau_p\nu_x - \tau_x\nu_p) > 0$. Because productivity has a positive effect on job creation, $\tau_x > 0$, and on market returns, $\nu_x > 0$, this condition reduces to $\tau_p > \nu_p$ which again emphasizes that the cash-flow effect of efficiency shocks has to dominate the discount rate effect.

C. Cross-Section of Returns

In the previous section, we have shown that labor market tightness obtains a negative factor risk premium in equilibrium. To assess to what extent our model can quantitatively explain the empirically observed negative relation between loadings on labor market tightness and future stock returns, we follow the empirical procedure in Section II on simulated data. To this end, we sort the simulated panel of firms into decile portfolios according to their labor market tightness loadings, $\beta_{i,t}^\theta$, as defined in Proposition 1. Table X compares the simulated return spread with the data on industry-neutral portfolios summarized in Table VII. As in the data, we form monthly value-weighted portfolios with annual rebalancing. The table reports average labor market tightness loadings, returns, and CAPM alphas across portfolios.

The model generates a realistic dispersion in labor market tightness loadings across portfolios. The average monthly return difference between the low- and high-loading portfolios is 0.36% relative to 0.37% in the data. Moreover, the CAPM cannot explain the return differences across portfolios because in the model it does not span all systematic risk. In

particular, Proposition 2 states that the CAPM alphas are inversely related with loadings on labor market tightness, as long as the market price of labor market tightness is negative.

The cash-flow channel of hiring costs impacts the cross-section of returns in the following way. Due to the proportional hiring and firing costs, the optimal firm policy exhibits regions of inactivity where firms neither hire nor fire workers. Figure 4 illustrates the optimal firm policy. The black line is the optimal policy when adjusting the workforce is costless. In the frictionless model, firms always adjust to the target employment size independent of the current size. The red curve is the optimal policy in the benchmark model. It displays two kinks. In the middle region where the optimal policy coincides with the 45 degree line, firms are inactive. In the inactivity region below the frictionless employment target, firms have too few workers but hiring is too costly. In the inactivity region above the frictionless employment target, firms have too many workers but firing is too costly.

Due to the time variation in matching efficiency, ideally, firms would like to hire when marginal hiring costs, $\kappa_h/q(\theta, p)$, are low. This holds for the majority of firms as vacancy postings increase with efficiency shocks. However, some firms are hit by low idiosyncratic productivity shocks such that hiring is not optimal when matching efficiency is high. For these firms, the employment policy is in the inaction region because the discount rate channel dominates the cash-flow channel. In addition, wages increase with labor market tightness, exacerbating low dividend payouts. 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 quantitatively replicate the negative relation between labor market tightness loadings and expected returns.

Selecting firms based on loadings on labor market conditions is informative about future returns whereas sorts based on hiring characteristics are not. In our model, the cost of hiring depends on labor market tightness but the employment growth rate characteristic does not control for this. This is why sorting firms by employment growth rates is not informative about future returns.

D. Comparative Statics

In Table XI, we shut down different channels of the model to gain a better understanding of our modeling assumptions. As in the previous table, we form decile portfolios based on labor market tightness loadings.

In the comparative statics experiments of Models (1) and (2), we change the pricing kernel. In Model (1), we assume that the matching efficiency shocks are not priced, $\gamma_{p,0} = 0$, and raise the price of productivity shocks to 10, $\gamma_x = 10$. As a result, the Sharpe ratio of the pricing kernel changes little but the return spread collapses to zero. Thus, the labor market tightness factor affects valuations via priced variation in matching efficiency. With only the productivity shocks priced, the cross-sectional spread is small and negative -0.09 . In order to analyze the time-variation of the price of risk of the matching efficiency shock, in Model (2), we set $\gamma_{p,1} = 0$, so that the aggregate p shock has constant price of risk. The simulated cross-sectional spread reduces from 0.36 to 0.22.

In Models (3) and (4), the matching efficiency shocks p and the aggregate productivity shocks x are turned off respectively so that Model (3) is only driven by aggregate productivity shocks and Model (4) only by matching efficiency shocks. Since they are both one factor models, we do not compute the multi-variate loadings as in Equation (3); rather, we compute the uni-variate loadings on labor market tightness. Consistent with the fact that labor market tightness is procyclical, in Model (3), LMT loads positively on aggregate productivity shocks and thus has a positive price of risk. This implication is inconsistent with the data, that means, negatively priced matching efficiency shock are crucial for the model mechanism to work. On the other hand, with only matching efficiency shocks, labor market tightness has a negative price of risk in Model (4). The portfolio spread has the correct sign but smaller magnitude, indicating the importance of including productivity shock to generate enough cross-sectional dispersion among firms.

In Models (5) to (9), we analyze the importance of the search frictions by changing the parameters related to the labor market. In Model (5), we set $\theta_t = \theta_{ss}$ in the wage process so that the wage rate does not depend on the labor market equilibrium. As a result, the wage rate

is less cyclical and the portfolio spread increases to 0.44. In Model (6), we increase the firm's bargaining power to $\eta = 0.5$ and adjust the size of the labor force to match unemployment rate of 5.8%. As the wage rate becomes more cyclical, the spread reduces to 0.18. Both findings indicate that the stickiness of the wage process as a result of the bargaining process contributes partly to the pricing power of the LMT factor.

To understand to what extent wedges created by search frictions drive the results, in Model (7), we set $\kappa_f = 0$ so that there is zero cost to downsize. The spread reduces to 0.31, indicating the frictions of downsizing is not the major driving force of the cross-sectional spread. In Model (8), we reduces κ_h from 0.4 to 0.3 and adjust the size of the labor force to match unemployment rate of 5.8%. The spread reduces from 0.36 to 0.32. This shows that the cost of hiring and not firing is the main driving force of the cross-sectional spread.

To analyze the effect of fixed operation cost, in Model (9), we set $f_0 = 0$. The simulated dividend to output ratio becomes 0.22, which is twice as large as the observed one. As a result, the cross-sectional spread reduces 0.15. This shows that matching the profit margin correctly is important for replicating the cross-sectional portfolio spread.

V. Conclusion

This paper analyzes the cross-sectional asset-pricing implications of a risk factor originating in the labor market. We first empirically document a robust negative relation between stock return loadings on changes in labor market tightness and future equity returns in the cross-section. We then develop a Labor Capital Asset Pricing Model with heterogeneous firms making dynamic employment decisions under labor search frictions which replicates the empirical facts.

We add two novel features to the standard labor search model. First, equilibrium labor market tightness is determined endogenously as the total number of optimal vacancies posted relative to the number of unemployed workers and depends on the time-varying firm-level distribution. Second, we assume that the efficiency of the matching technology is stochastic. As an equilibrium outcome, labor market tightness is positively related with efficiency shocks.

Consequently, firms with low labor market tightness loadings are very sensitive to labor market conditions that originate from matching efficiency shocks. These firms have cash flows which are not hedged against positive efficiency shocks and hence require a high expected stock returns.

Appendix

A. Data

We describe the definitions of control variables in the Fama-MacBeth regressions of section II.E. The regressions use stock returns from July of year t to June of year $t + 1$ as dependent variables. We also provide definitions for firm characteristics studied in section II. Compustat data items are listed in parentheses where appropriate.

ME is the natural logarithm of market equity of the firm, calculated as the product of its price per share and number shares outstanding at the end of June of calendar year t .

BM is the natural logarithm of the ratio of book equity to market equity for the fiscal year ending in calendar year $t - 1$. 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 the 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). Market equity used to compute the book-to-market ratio is the product of the price and the number of shares outstanding at the end of December of calendar year $t - 1$.

RU is the stock return runup over twelve months ending in June of year t .

HN is the hiring rate, calculated following Belo, Lin, and Bazdresch (2013) as $(N_{t-1} - N_{t-2}) / ((N_{t-1} + N_{t-2}) / 2)$, where N_t is then number of employees (EMP) at the end of the fiscal year ending in calendar year t .

AG is the asset growth rate, calculated following Cooper, Gulen, and Schill (2008) as $A_{t-1} / A_{t-2} - 1$, where A_t is then value of total assets (AT) at the end of the fiscal year ending in calendar year t .

IK is the investment rate, calculated following Belo, Lin, and Bazdresch (2013) as the ratio of capital expenditure (CAPX) during the fiscal year ending in calendar year $t - 1$ divided by

fiscal year $t - 2$ capital stock (PPENT).

Cash Flow 1 is defined following Cooper, Gulen, and Schill (2008) as [operating income before depreciation (OIBDP) - interest expenses (XINT) - taxes (TXT) - preferred dividends (DVP) - common dividends (DVC)] / total assets (AT).

Cash Flow 2 is defined by modifying Cooper, Gulen, and Schill (2008) definition to exclude dividends: [operating income before depreciation (OIBDP) - interest expenses (XINT) - taxes (TXT)] / total assets (AT).

Return on assets is defined following Cooper, Gulen, and Schill (2008) as operating income before depreciation (OIBDP) scaled by total assets (AT).

B. Wages

In this section, we derive the Nash bargaining wage equation, in the spirit of Stole and Zwiebel (1996) and Kuehn, Petrosky-Nadeau, and Zhang (2012). Denote $S_{V_{i,t}}$ the marginal value of a vacancy posting for a firm that posts positive vacancies. Let $\frac{\partial S_{i,t}^H}{\partial N_{i,t}}$, $\frac{\partial S_{i,t}^I}{\partial N_{i,t}}$, and $\frac{\partial S_{i,t}^F}{\partial N_{i,t}}$ be respectively the marginal values of an incumbent worker to a hiring firm, an inaction firm, and a firing firm. For a hiring firm, take the first order condition with respect to $N_{i,t+1}$, and apply the free entry conditions $S_{V_{i,t}} = 0$, we obtain

$$\frac{\partial S_{i,t}}{\partial V_{i,t}} = -\frac{\kappa_h}{q(\theta_t, p_t)} + \mathbb{E}_t \left[M_{t+1} S_{N_{i,t+1}}^H \right] = 0. \quad (37)$$

We consider a stable outcome profile characterized in Stole and Zwiebel (1996). If the marginal worker leaves, the firm immediately loses the marginal product net of her wage payment. In addition, a wage renegotiation ensues with the remaining employee, which leads to a change in wage payment. In other words, the firm not only benefits from hiring the marginal worker through an increase in output by the marginal product of labor, but also an adjustment in the wage payment to all the existing workers. That is

$$\frac{\partial S_{i,t}}{\partial N_{i,t}} = \frac{\partial Y_{i,t}}{\partial N_{i,t}} - w_{i,t} - \frac{\partial w_{i,t}}{\partial N_{i,t}} N_{i,t} + (1 - s) \mathbb{E}_t \left[M_{t+1} S_{N_{i,t+1}} \right], \quad (38)$$

where $S_{N_{i,t+1}}$ denote the marginal value of an incumbent worker at time $t + 1$.

In order to perform Nash bargaining over the total surplus of a match, we need to specify the marginal utilities to an employed and an unemployed worker. Since we do not model the household size, let us assume a hypothetical representative family that makes decisions on the extensive margin. ϕ_t is the marginal utility of the family that transforms money benefit to utils. Denote $J_{N_{i,t}}$ the marginal utility of an employed worker to the representative family, and $J_{V_{i,t}}$ the marginal value of an unemployed worker to the family. An unemployed worker receives the unemployment benefit b for the current period. She has a probability $f(\theta_t)$ of finding a job at a hiring firm next period. We can write the following recursive form for $J_{U_{i,t}}$

$$\frac{J_{U_{i,t}}}{\phi_t} = b + \mathbb{E}_t \left[M_{t+1} \left(f(\theta_t) \frac{J_{N_{i,t+1}}^H}{\phi_{t+1}} + (1 - f(\theta_t)) \frac{J_{U_{i,t+1}}}{\phi_{t+1}} \right) \right]. \quad (39)$$

Given workers' bargaining power η , Nash bargaining at time $t + 1$ between the newly matched worker and the hiring firm satisfies the following

$$\frac{J_{N_{i,t+1}} - J_{U_{i,t+1}}}{\phi_{t+1}} = \eta \left[\frac{J_{N_{i,t+1}} - J_{U_{i,t+1}}}{\phi_{t+1}} + S_{N_{i,t+1}}^H - S_{V_{i,t+1}} \right]. \quad (40)$$

Combine (40) with (37), and plug in (39), we have

$$\frac{J_{U_{i,t}}}{\phi_t} = b + \mathbb{E} \left[M_{t+1} \frac{J_{U_{i,t+1}}}{\phi_{t+1}} \right] + f(\theta_t) \frac{\eta}{1 - \eta} \frac{\kappa_h}{q(\theta_t, p_t)}. \quad (41)$$

An employed worker receives $w_{i,t}$ for period t , and has probability s of quitting the job next period. We can write $J_{N_{i,t}}$ recursively

$$\begin{aligned} \frac{J_{N_{i,t}}}{\phi_t} &= w_{i,t} + \mathbb{E}_t \left[M_{t+1} \left((1 - s) \frac{J_{N_{i,t+1}}}{\phi_{t+1}} + s \frac{J_{U_{i,t+1}}}{\phi_{t+1}} \right) \right] \\ &= w_{i,t} + \mathbb{E}_t \left[M_{t+1} \frac{J_{U_{i,t+1}}}{\phi_{t+1}} \right] + \frac{\eta}{1 - \eta} (1 - s) \mathbb{E}_t [M_{t+1} S_{N_{i,t+1}}]. \end{aligned} \quad (42)$$

The last step follows from Nash bargaining at time $t + 1$ between the remaining worker and her firm, which is potentially hiring, firing or neither of the two.

Plug (38), (41), (42) into $\frac{J_{N_{i,t}} - J_{U_{i,t}}}{\phi_t} = \frac{\eta}{1 - \eta} [S_{N_{i,t}} - S_{V_{i,t}}]$, and notice $\theta_t = \frac{f(\theta_t)}{q(\theta_t, p_t)}$. We conclude that the wage rate $w_{i,t}$ must satisfy the differential equation

$$w_{i,t} - b = \eta \left[\frac{\partial Y_{i,t}}{\partial N_{i,t}} - \frac{\partial w_{i,t}}{\partial N_{i,t}} N_{i,t} + \kappa_h \theta_t \right] + (1 - \eta)b. \quad (43)$$

The wage rate is solved as

$$w_{i,t} = \eta \left[\frac{\alpha}{1 - \eta(1 - \alpha)} \frac{Y_{i,t}}{N_{i,t}} + \kappa_h \theta_t \right] + (1 - \eta)b \quad (44)$$

C. The Labor CAPM

Proof of Proposition 1: A log-linear approximation of a pricing kernel is given by

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

Given the Euler equation $\mathbb{E}_t[M_{t+1}R_{t+1}^e] = 0$, this implies

$$\mathbb{E}_t[R_{i,t+1}^e] = -\text{Cov}_t(m_{t+1}, R_{t+1}^e) \quad (45)$$

For the pricing kernel (17), this implies

$$\mathbb{E}_t[R_{i,t+1}^e] = \gamma_x \text{Cov}_t(x_{t+1}, R_{i,t+1}^e) + \gamma_p \text{Cov}_t(p_{t+1}, R_{i,t+1}^e) \quad (46)$$

$$= \beta_{i,t}^x \lambda^x + \beta_{i,t}^p \lambda_t^p \quad (47)$$

where risk loadings are given by

$$\beta_{i,t}^x = \frac{\text{Cov}_t(x_{t+1}, R_{i,t+1}^e)}{\sigma_x^2} \quad \beta_{i,t}^p = \frac{\text{Cov}_t(p_{t+1}, R_{i,t+1}^e)}{\sigma_p^2}, \quad (48)$$

and factor risk premia are

$$\lambda^x = \gamma_x \sigma_x^2 \quad \lambda_t^p = \gamma_{p,t} \sigma_p^2. \quad (49)$$

Given the pricing kernel (27) and laws of motions (24) and (26), it follows from (45) that

$$\mathbb{E}_t[R_{i,t+1}^e] = (\gamma_{M,t}\nu_x + \gamma_{\theta,t}\tau_x)\text{Cov}_t(x_{t+1}, R_{i,t+1}^e) + (\gamma_{\theta,t}\tau_p + \gamma_{M,t}\nu_p)\text{Cov}_t(p_{t+1}, R_{i,t+1}^e). \quad (50)$$

Thus, by matching coefficients in terms of covariance of (46) and (48), it follows that

$$\gamma_x = \gamma_{M,t}\nu_x + \gamma_{\theta,t}\tau_x \quad \gamma_{p,t} = \gamma_{\theta,t}\tau_p + \gamma_{M,t}\nu_p$$

implying (28) holds.

Since x_t and p_t are uncorrelated, the factor loadings β^x and β^p satisfy the regression

$$R_{i,t+1}^e - \mathbb{E}_t[R_{i,t+1}^e] = \beta_{i,t}^x(x_{t+1} - \rho_x x_t) + \beta_{i,t}^p(p_{t+1} - \rho_p p_t) + \epsilon_{i,t+1}, \quad (51)$$

with loadings defined in equation (48). Similarly, the loadings on the market return and labor market tightness satisfy the regression

$$R_{i,t+1}^e - \mathbb{E}_t[R_{i,t+1}^e] = \beta_{i,t}^M (R_{M,t+1}^e - \mathbb{E}_t[R_{M,t+1}^e]) + \beta_{i,t}^\theta (\vartheta_{t+1} - \mathbb{E}_t[\vartheta_{t+1}]) + \epsilon_{i,t+1}. \quad (52)$$

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

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

To compute the loadings on the market return and labor market tightness, equate equations (51) and (52) and substitute in laws of motion (24) and (26), thus,

$$\begin{aligned} \beta_{i,t}^x(x_{t+1} - \rho_x x_t) + \beta_{i,t}^p(p_{t+1} - \rho_p p_t) + \epsilon_{i,t+1} = \\ \beta_{i,t}^M(\nu_x(x_{t+1} - \rho_x x_t) + \nu_p(p_{t+1} - \rho_p p_t)) + \beta_{i,t}^\theta(\tau_x(x_{t+1} - \rho_x x_t) + \tau_p(p_{t+1} - \rho_p p_t)) + \epsilon_{i,t+1}. \end{aligned}$$

By matching the coefficients in terms of $(x_{t+1} - \rho_x x_t)$ and $(p_{t+1} - \rho_p p_t)$, we get

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

implying that (30) and (31) hold.

Next, substitute (30) and (31) into (29)

$$\mathbb{E}_t[R_{i,t+1}^e] = \frac{\tau_x \beta_{i,t}^p - \tau_p \beta_{i,t}^x}{\nu_p \tau_x - \nu_x \tau_p} \lambda_t^M + \frac{\nu_p \beta_{i,t}^x - \nu_x \beta_{i,t}^p}{\nu_p \tau_x - \nu_x \tau_p} \lambda_t^\theta \quad (53)$$

and matching the coefficients of $\beta_{i,t}^x$ and $\beta_{i,t}^p$ with (47) implies

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

Solving for λ_t^θ and λ_t^M confirms (32).

Proof of Proposition 2: Given (26), univariate loadings on the market return can be computed via

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

Notice that the CAPM factor risk premium stays the same in the factor or multi-factor models, that is, $\lambda_t^{CAPM} = \lambda_t^M = \nu_x \lambda^x + \nu_p \lambda_t^p$. Given the pricing of expected excess returns in

terms of independent aggregate risks, $\mathbb{E}_t[R_{i,t+1}^e] = \beta_{i,t}^x \lambda_t^x + \beta_{i,t}^p \lambda_t^p$, we can calculate the CAPM mispricing as

$$\alpha_{i,t}^{CAPM} = \beta_{i,t}^x \lambda_t^x + \beta_{i,t}^p \lambda_t^p - \beta_{i,t}^{CAPM} \lambda_t^{CAPM} = \frac{\left(\beta_{i,t}^x \nu_p - \beta_{i,t}^p \nu_x\right) (\nu_p \gamma_x - \nu_x \gamma_p) \sigma_x^2 \sigma_p^2}{\nu_x^2 \sigma_x^2 + \nu_p^2 \sigma_p^2}.$$

Using the definition of $\beta_{i,t}^\theta$ in (31) and $\gamma_{\theta,t}$ in (28), it follows that (34) holds.

D. Computational Algorithm

To solve the model numerically, we discretize the state space. All shocks (x, z, p) follow finite states Markov chains according to Rouwenhorst (1995) with 5 states for x , 11 for z and 5 for p . We create an evenly spaced grid of 50 points for employment N in the interval $[0.01, 5.0]$. The lower and upper bounds of N are set such that the optimal policies are not binding in the simulation¹⁶. The space of the labor market tightness θ needs to be transformed into a discrete space as well. We use an evenly spaced grid in the interval $[0.25, 1.25]$ with 30 points. The upper bound for θ is chosen such that the simulated paths of equilibrium labor market tightness never step outside the bounds. The choice variable N' is a vector containing 5000 elements evenly spaced on the interval $[0.01, 5.0]$. We use linear interpolation to obtain the value function off grid points. Our results are robust to a higher numbers of the grid points, non-evenly spaced grids, and nonlinear interpolation methods.

The computation algorithm amounts to the following iterative procedure:

1. Initial guess: Take an initial guess for the coefficient vector τ in the law of motion (23). Since the time series of θ_t is procyclical and highly persistent, we start from $\tau = (-0.23; 0.5; 0; 0; 1; 0)$. At steady state, $\tau_0 = (1 - \tau_\theta) \log \theta^{ss} = -0.23$.
2. Optimization: Solve the firm's optimization problem (19) given the forecasting rule coefficients τ . For this step we use value function iteration. Specifically, the firm value function solves

$$S(N, z, x, p, \theta) = \max\{S(N, z, x, p, \theta)^h, S(N, z, x, p, \theta)^f\}, \quad (54)$$

¹⁶In this heterogeneous firms model, as long as the aggregate employment rate is well-defined in $[0, 1]$, individual firm size is not bounded by 1 as in the case of representative firm models.

where

$$S(N, z, x, p, \theta)^h = \max_{N' \geq (1-s)N} \{(1-\eta)e^{x+z}N^\alpha - [\eta\kappa_h\theta + (1-\eta)b]N - \frac{\kappa_h}{q(\theta)}[N' - (1-s)N] + \mathbb{E}[M'S(N', z', x', p', \theta')|z, N, x, p, \theta]\}, \quad (55)$$

and

$$S(N, z, x, p, \theta)^f = \max_{N' \leq (1-s)N} \{(1-\eta)e^{x+z}N^\alpha - [\eta\kappa_h\theta + (1-\eta)b]N - \kappa_f[(1-s)N - N'] + \mathbb{E}[M'S(N', z', x', p', \theta')|z, N, x, p, \theta]\}. \quad (56)$$

3. Simulation: Use the firm's optimal employment policies $V(N, z, x, p, \theta)$ and $F(N, z, x, p, \theta)$ to simulate a panel of $N = 5000$ firms over $T = 5300$ periods. Here we emphasize that at each period, we impose labor market equilibrium by solving θ_t as the fixed point in Equation (22). In this fashion, we obtain a time series of realized θ_t .
4. Update coefficients: we truncate the initial 300 months as burn-in periods, and use the stationary region of the simulated data to estimate the vector τ by OLS. Update the forecasting coefficients, and restart from the optimization step. Continue the outer loop iteration until the coefficients converge and the goodness-of-fit measures are satisfactory.

References

- Andolfatto, David, 1996, Business cycles and labor-market search, *American Economic Review* 86, 112–32.
- Asness, Clifford S., R. Burt, Porter Ross, and L. Stevens, 2000, Predicting stock returns using industry-relative firm characteristics, Working paper.
- Barnichon, Regis, 2010, Building a composite help-wanted index, *Economics Letters* 109, 175–178.
- , and Andrew Figura, 2011, Labor market heterogeneities and the aggregate matching function, Working paper.
- Beauchemin, Kenneth, and Murat Tasci, 2012, Diagnosing labor market search models: a multiple-shock approach, *Macroeconomic Dynamics* forthcoming.
- Belo, Frederico, Xiaoji Lin, and Santiago Bazdresch, 2013, Labor hiring, investment, and stock return predictability in the cross section, *Journal of Political Economy* Forthcoming.
- Berk, Jonathan, Richard C. Green, and Vasant Naik, 1999, Optimal investment, growth options, and security returns, *Journal of Finance* 54, 1553–1607.
- Boguth, Oliver, Murray Carlson, Adlai Fisher, and Mikhail Simutin, 2011, Conditional risk and performance evaluation: Volatility timing, overconditioning, and new estimates of momentum alphas, *Journal of Financial Economics* 102, 363–389.
- Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.
- Carlson, Murray, Adlai Fisher, and Ron Giammarino, 2004, Corporate investment and asset price dynamics: Implications for the cross-section of returns, *Journal of Finance* 59, 2577–2603.
- Chen, Huafeng Jason, Marcin Kacperczyk, and Hernn Ortiz-Molina, 2011, Labor unions, operating flexibility, and the cost of equity, *Journal of Financial and Quantitative Analysis* 46, 25–58.
- Cheremukhin, Anton A., and Paulina Restrepo-Echavarria, 2010, The labor wedge as a matching friction, Working paper.
- Cochrane, John H., 1991, Production-based asset pricing and the link between stock returns and economic-fluctuations, *Journal of Finance* 46, 209–237.
- Cohen, Randolph B., and Christopher Polk, 1998, The impact of industry factors in asset-pricing tests, Working paper.
- Cooper, Ilan, 2006, Asset pricing implications of non-convex adjustment costs of investment, *Journal of Finance* 61, 139–170.
- Cooper, Michael J., Huseyin Gulen, and Michael S. Schill, 2008, Asset growth and the cross-section of stock returns, *Journal of Finance* 63, 1609–1651.
- Cooper, Russell, John Haltiwanger, and Jonathan L. Willis, 2007, Search frictions: Matching aggregate and establishment observations, *Journal of Monetary Economics* 54, 56–78.
- Danthine, Jean-Pierre, and John B. Donaldson, 2002, Labor relation and asset returns, *Review of Economic Studies* 69, 41–64.
- Davis, James L., Eugene F. Fama, and Kenneth R. French, 2000, Characteristics, covariances, and average returns: 1929 to 1997, *Journal of Finance* 55, 389–406.

- Davis, Steven J., Jason R. Faberman, John C. Haltiwanger, and Ian Rucker, 2010, Adjusted estimates of worker flows and job openings in JOLTS, in Katharine G. Abraham, James R. Spletzer, and Michael J. Harper, ed.: *Labor in the New Economy* . pp. 187–216 (University of Chicago Press).
- Davis, Steven J., R. Jason Faberman, and John Haltiwanger, 2006, The flow approach to labor markets: New data sources and micro-macro links, *Journal of Economic Perspectives* 20, 3–26.
- Davis, Steven J., John Haltiwanger, Ron Jarmin, and Javier Miranda, 2006, Volatility and dispersion in business growth rates: Publicly traded versus privately held firms, *NBER Macroeconomics Annual* 21, 107–179.
- den Haan, Wouter J., Garey Ramey, and Joel Watson, 2000, Job destruction and propagation of shocks, *American Economic Review* 90, 482–498.
- Diamond, Peter A, 1982, Wage determination and efficiency in search equilibrium, *Review of Economic Studies* 49, 217–27.
- Donangelo, Andres, 2012, Labor mobility: Implications for asset pricing, *Journal of Finance* forthcoming.
- Eisfeldt, Andrea, and Dimitris Papanikolaou, 2013, Organization capital and the cross-section of expected returns, *Journal of Finance* 68, 1365–1406.
- Elsby, Michael W. L., and Ryan Michaels, 2013, Marginal jobs, heterogeneous firms, and unemployment flows, *American Economic Journal: Macroeconomics* 5, 1–48.
- Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427–465.
- , 1993, Common risk-factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.
- Fama, Eugene F., and James D. MacBeth, 1973, Risk, return, and equilibrium - empirical tests, *Journal of Political Economy* 81, 607–636.
- Favilukis, Jack, and Xiaoji Lin, 2012, Wage rigidity: A solution to several asset pricing puzzles, Working Paper.
- Ferson, Wayne E, and Rudi W Schadt, 1996, Measuring fund strategy and performance in changing economic conditions, *Journal of Finance* 51, 425–461.
- Fujita, Shigeru, 2011, Effects of extended unemployment insurance benefits: evidence from the monthly CPS, Working paper.
- , and Makoto Nakajima, 2013, Worker flows and job flows: A quantitative investigation, FRB of Philadelphia Working paper.
- Furlanetto, Francesco, and Nicolas Groshenny, 2012, Matching efficiency and business cycle fluctuations, CAMA Working paper.
- Gertler, Mark, and Antonella Trigari, 2009, Unemployment fluctuations with staggered nash wage bargaining, *Journal of Political Economy* 117, 38–86.
- Gomes, Joao, Leonid Kogan, and Lu Zhang, 2003, Equilibrium cross section of returns, *Journal of Political Economy* 111, 693–732.
- Gomes, Joao F., and Lukas Schmid, 2010, Levered returns, *Journal of Finance* 65, 467–494.

- Gomme, Paul, and Peter Rupert, 2007, Theory, measurement and calibration of macroeconomic models, *Journal of Monetary Economics* 54, 460–497.
- Gourio, François, 2007, Labor leverage, firms’ heterogeneous sensitivities to the business cycle, and the cross-section of expected returns, Working paper.
- Hagedorn, Marcus, and Iourii Manovskii, 2008, The cyclical behavior of equilibrium unemployment and vacancies revisited, *American Economic Review* 98, 1692–1706.
- Hall, Robert E., 2005, Employment fluctuations with equilibrium wage stickiness, *American Economic Review* 95, 50–65.
- , and Paul R. Milgrom, 2008, The limited influence of unemployment on the wage bargain, *American Economic Review* 98, 1653–74.
- Herz, Benedikt, and Thijs van Rens, 2011, Accounting for mismatch unemployment, Working paper.
- Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers - implications for stock-market efficiency, *Journal of Finance* 48, 65–91.
- Jermann, Urban J., 1998, Asset pricing in production economies, *Journal of Monetary Economics* 41, 257–275.
- Kogan, Leonid, and Dimitris Papanikolaou, 2012, Growth opportunities, technology shocks, and asset prices, *Journal of Finance* Forthcoming.
- , 2013, Firm characteristics and stock returns: The role of investment-specific shocks, *Review of Financial Studies* Forthcoming.
- Krusell, Per, and Jr. Smith, Anthony A., 1998, Income and wealth heterogeneity in the macroeconomy, *Journal of Political Economy* 106, 867–96.
- Kuehn, Lars-Alexander, Nicolas Petrosky-Nadeau, and Lu Zhang, 2012, An equilibrium asset pricing model with labor market search, NBER Working paper.
- Lubik, Thomas A., 2009, Estimating a search and matching model of the aggregate labor market, *Economic Quarterly* pp. 101–120.
- Merz, Monika, 1995, Search in the labor market and the real business cycle, *Journal of Monetary Economics* 36, 269–300.
- , and Eran Yashiv, 2007, Labor and the market value of the firm, *American Economic Review* 97, 1419–1431.
- Mortensen, Dale T., 1982, The matching process as a noncooperative bargaining game, in *The Economics of Information and Uncertainty* . pp. 233–258 (NBER).
- , 2010, Wage dispersion in the search and matching model, *American Economic Review* 100, 338–42.
- Mortensen, Dale T, and Christopher A Pissarides, 1994, Job creation and job destruction in the theory of unemployment, *Review of Economic Studies* 61, 397–415.
- Newey, Whitney K., and Kenneth D. West, 1987, A simple, positive semidefinite, heteroskedasticity and autocorrelation consistent covariance-matrix, *Econometrica* 55, 703–708.
- Novy-Marx, Robert, 2011, Operating leverage, *Review of Finance* 39, 103–134.

- Papanikolaou, Dimitris, 2011, Investment shocks and asset prices, *Journal of Political Economy* 119, 639–685.
- Pissarides, Christopher A., 1985, Short-run equilibrium dynamics of unemployment, vacancies, and real wages, *American Economic Review* 75, 676–690.
- , 2009, The unemployment volatility puzzle: Is wage stickiness the answer?, *Econometrica* 77, 1339–1369.
- , 2011, Equilibrium in the labor market with search frictions, *American Economic Review* 101, 1092–1105.
- Sahin, Aysegul, Joseph Song, Giorgio Topa, and Giovanni L. Violante, 2012, Mismatch unemployment, NBER Working paper.
- Shimer, Robert, 2005, The cyclical behavior of equilibrium unemployment and vacancies, *American Economic Review* 95, 25–49.
- Simutin, Mikhail, 2010, Excess cash and stock returns, *Financial Management* 39, 1197–1222.
- Sterk, Vincent, 2010, Home equity, mobility, and macroeconomic fluctuations, DNB Working paper.
- Stole, Lars A., and Jeffrey Zwiebel, 1996, Intra-firm bargaining under non-binding contracts, *Review of Economic Studies* 63, 375–410.
- Zhang, Lu, 2005, The value premium, *Journal of Finance* 60, 67–103.

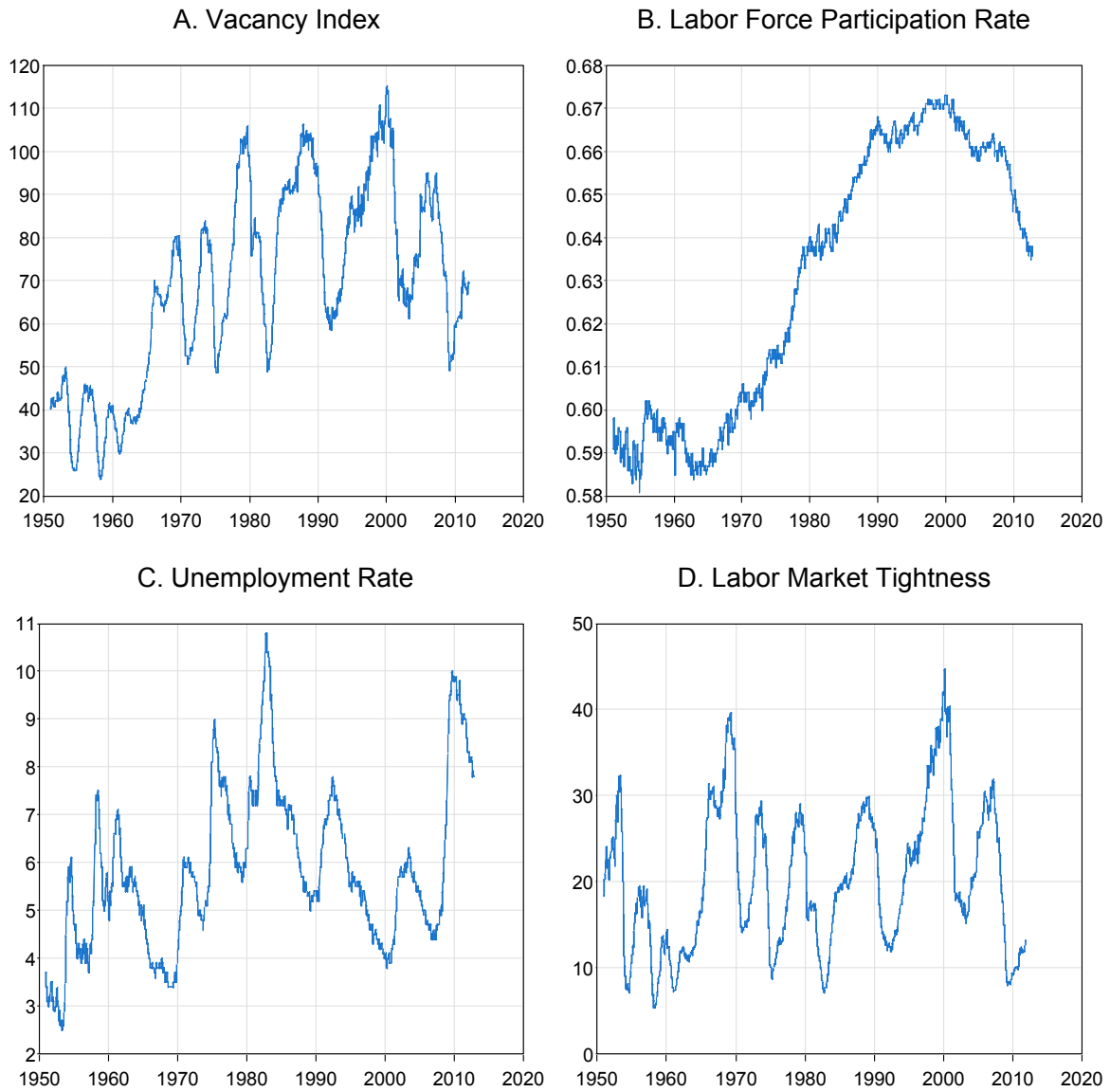
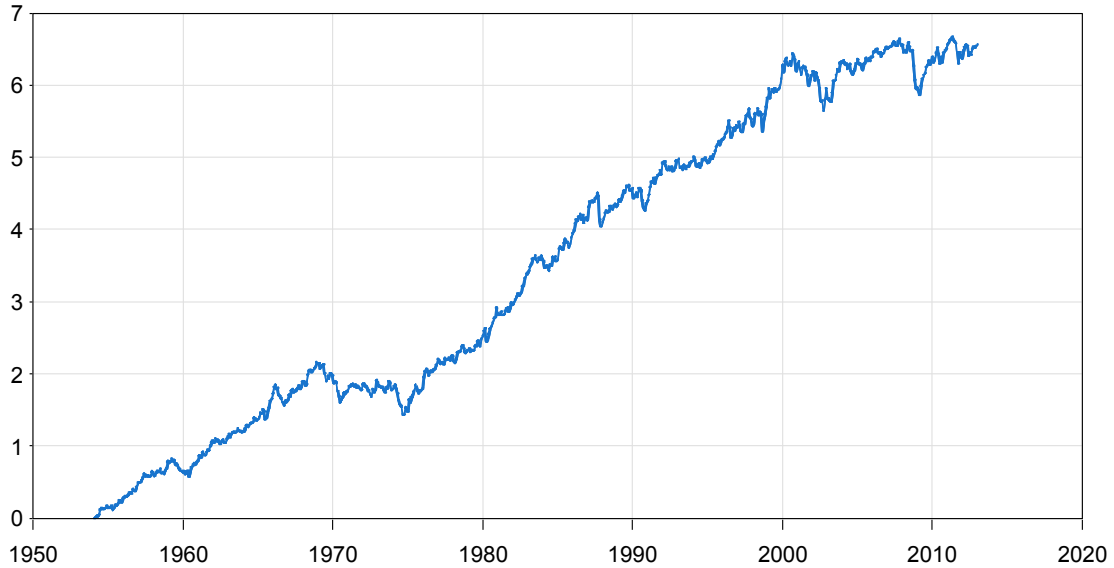


Figure 1. Labor Market Tightness and Its Components

This figure plots the monthly time series of the vacancy index, the labor force participation rate, the unemployment rate, and the labor market tightness.

A. Log Cumulative Return of the Low - High Portfolio



B. Monthly Return of the Low - High Portfolio

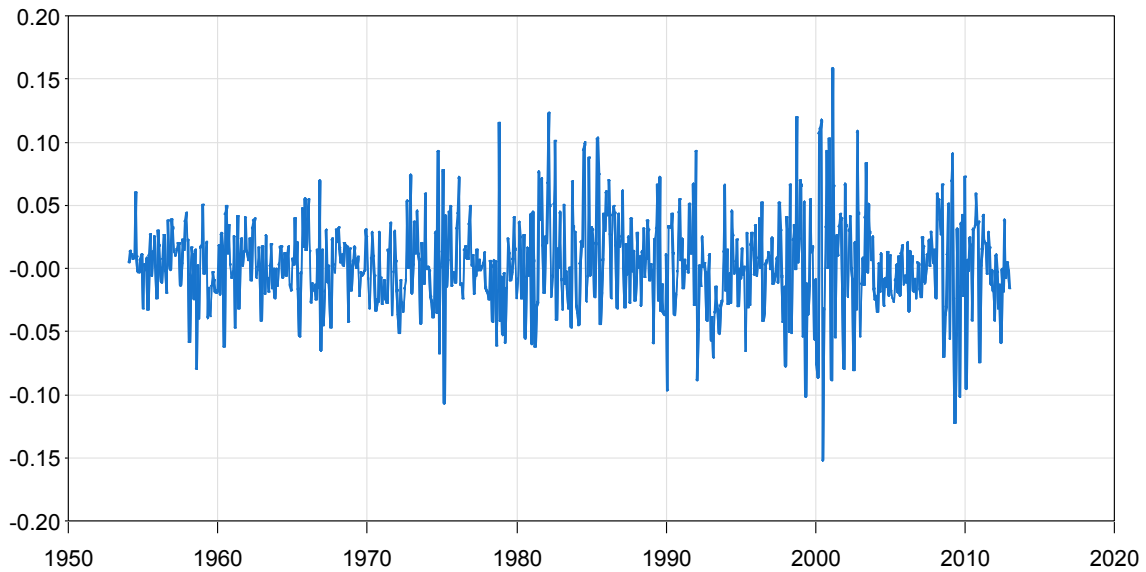


Figure 2. Returns of the Labor Market Tightness Factor

This figure plots in Panel A the log cumulative return of the portfolio that longs the decile of stocks with the lowest exposure to the labor market tightness factor and shorts the decile of stocks with the highest loadings and plots in Panel B the monthly returns of this portfolio.

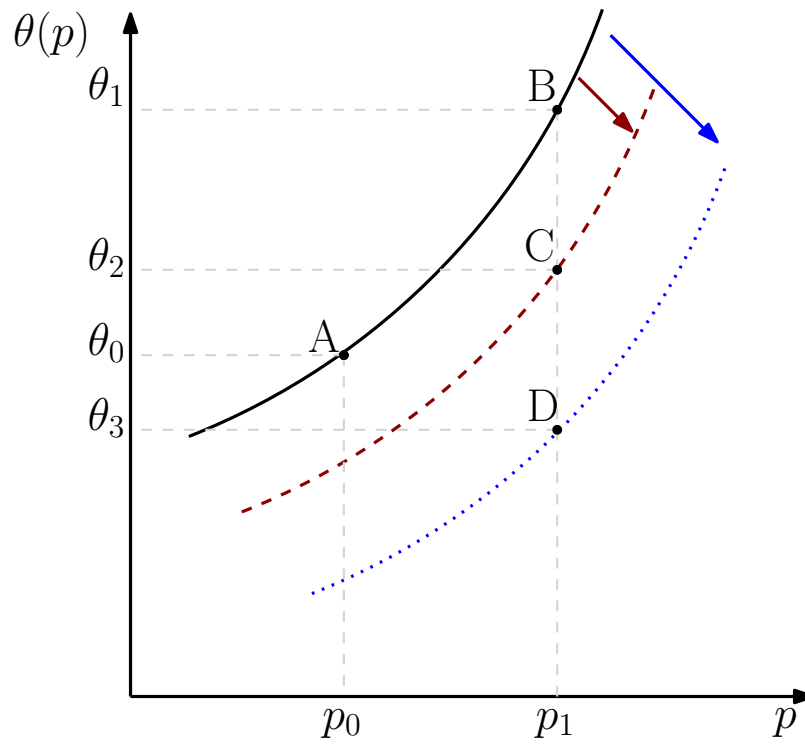


Figure 3. Labor Market Tightness and Efficiency Shock

This figure illustrates the endogenous relation between equilibrium labor market tightness, $\theta(p)$, and efficiency shocks, p , to the matching technology.

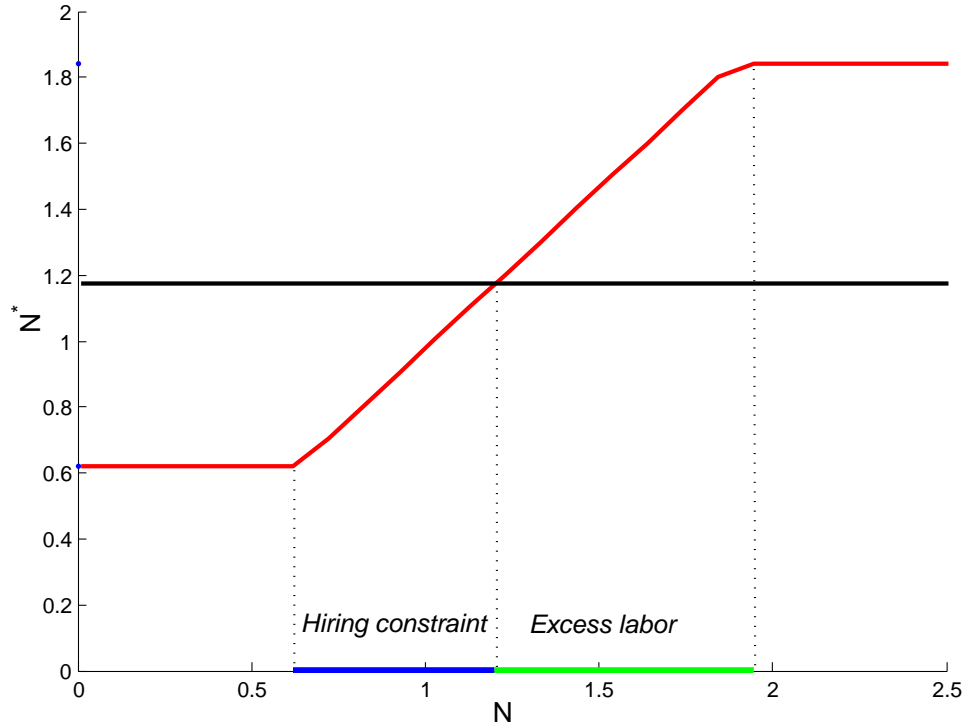


Figure 4. Optimal Employment Policies for a Firm under Search Frictions

This figure demonstrates the optimal labor adjustment policies for a firm under labor search frictions. The horizontal axis plots the firm’s current employment level N , and the vertical axis indicates the optimal future employment level N^* , keeping firm’s other state variables (x, p, θ, z) fixed. The black horizontal line indicates the optimal future employment level in a frictionless environment, which is independent of the current employment N . In contrast, the solid red curve N^* depicts the optimal policies under search frictions. The region *Hiring constraint* denotes firms who wish to, but cannot refill their lost workers. The region *Excess labor* consists firms who wish to, but cannot discharge its workforce. The sum of the two regions are referred to as the *Inaction region*, in which firms do not adjust the employee size freely.

Table I
Summary Statistics

This table reports summary statistics for the monthly labor market tightness factor (ϑ), change in the vacancy index (VAC), change in the unemployment rate (UNEMP), change in the labor force participation rate (LFPR), change in the industrial production (IP), change in the consumer price index (CPI), dividend yield (DY), T-bill rate (TB), term spread (TS), and default spread (DS) calculated for the 1954-2012 period. Means and standard deviations are in percent.

	Mean	St dev	Correlations										
			ϑ	VAC	UNEMP	LFPR	IP	CPI	DY	TB	TS	DS	
ϑ	0.02	5.48											
VAC	-0.10	3.46	0.78										
UNEMP	0.16	3.38	-0.83	-0.36									
LFPR	0.01	0.30	-0.13	0.04	0.15								
IP	0.24	0.89	0.56	0.44	-0.48	0.04							
CPI	0.31	0.32	-0.08	-0.04	0.06	0.05	-0.08						
DY	3.20	1.13	-0.14	0.00	0.12	0.07	-0.10	0.34					
TB	0.39	0.24	-0.12	-0.08	0.04	0.05	-0.09	0.52	0.51				
TS	1.45	1.22	0.11	0.10	-0.05	-0.03	0.04	-0.29	-0.12	-0.39			
DS	0.99	0.45	-0.26	-0.20	0.22	-0.03	-0.28	0.11	0.33	0.33	0.29		

Table II
Characteristics of Labor Market Tightness Portfolios

This table reports average characteristics for the ten portfolios of stocks sorted by their loadings on the labor market tightness factor, β^θ . β^M is market beta; BM is the book-to-market ratio; ME is the market equity decile; RU is the 12-month return runup, in percent; AG, IK, and HN are the asset growth, investment, and new hiring rates, respectively, all shown in percent. Mean characteristics are calculated in each annual cross-section and then averaged. The sample period is 1954-2012 except for variables that use Compustat data (BM, AG, IK, and HN) where it is 1960-2012.

Decile	β^θ	β^M	BM	ME	RU	AG	IK	HN
Low	-0.80	1.35	0.89	4.84	15.44	12.92	32.59	6.36
2	-0.38	1.16	0.92	5.73	13.68	13.02	29.39	7.16
3	-0.23	1.07	0.91	6.09	12.67	11.01	27.34	5.70
4	-0.12	1.01	0.92	6.27	12.92	11.36	27.05	6.72
5	-0.03	1.00	0.92	6.22	13.37	11.17	26.08	5.00
6	0.06	1.01	0.94	5.99	13.08	11.51	26.44	5.12
7	0.16	1.04	0.94	5.84	13.35	11.30	27.35	5.94
8	0.27	1.08	0.95	5.52	13.55	11.41	28.17	5.50
9	0.45	1.17	0.94	4.98	13.71	12.23	29.54	6.95
High	0.91	1.33	0.92	3.99	16.13	12.63	32.87	6.86

Table III
Performance of Labor Market Tightness Portfolios

This table reports average raw returns and alphas, in percent per month, and loadings from the four-factor model regressions for the ten 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 group. The bottom row gives t -statistics for the low-high portfolio. Firms are assigned into deciles at the end of every month τ and the value-weighted portfolios are held without rebalancing for 12 months beginning in month $\tau + 2$. Conditional alphas are intercepts from regression $R_{j,t} - R_{f,t} = \alpha_j + \beta_j [1 \ Z_{t-1}]' (R_{M,t} - R_{f,t}) + e_{j,\tau}$, 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. Ferson and Schadt (FS) conditional alpha is computed using as instruments demeaned dividend yield, term spread, T-bill rate, and default spread. Boguth, Carlson, Fisher, and Simutin (BCFS) 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. The sample period is 1954-2012.

Decile	Raw	Unconditional Alphas			Cond. Alphas		4-Factor Loadings			
	Return	CAPM	3-Factor	4-Factor	FS	BCFS	MKT	HML	SMB	UMD
Low	1.12	0.04	0.06	0.04	0.08	0.08	1.16	-0.11	0.38	0.02
2	1.09	0.13	0.13	0.13	0.11	0.11	1.05	0.01	-0.02	0.00
3	1.05	0.13	0.11	0.13	0.11	0.10	0.99	0.06	-0.08	-0.02
4	1.01	0.11	0.09	0.09	0.10	0.10	0.95	0.07	-0.10	-0.01
5	0.98	0.09	0.05	0.03	0.06	0.05	0.96	0.13	-0.11	0.01
6	0.96	0.06	0.03	0.01	0.04	0.04	0.97	0.09	-0.11	0.03
7	0.96	0.05	0.03	0.04	0.03	0.03	0.98	0.04	-0.07	-0.01
8	0.94	-0.01	-0.02	0.03	-0.01	0.00	1.01	0.00	0.02	-0.05
9	0.83	-0.20	-0.19	-0.13	-0.16	-0.14	1.11	-0.08	0.18	-0.07
High	0.65	-0.47	-0.46	-0.37	-0.40	-0.38	1.18	-0.19	0.62	-0.09
Low-High	0.47	0.51	0.52	0.41	0.48	0.47	-0.02	0.07	-0.24	0.11
t-statistic	[3.41]	[3.78]	[3.83]	[2.99]	[3.56]	[3.46]	[-0.62]	[1.41]	[-5.18]	[3.30]

Table IV
Summary Statistics of 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 market excess return, and value, size and momentum factors. All data are monthly. Means and standard deviations are in percent. The sample period is 1954-2012.

	Mean	Standard deviation	Sharpe ratio	Correlations			
				Low-high β^θ return	Mkt excess return	Value factor	Size factor
Low-high β^θ return	0.46	3.60	0.13				
Market excess return	0.55	4.40	0.13	-0.11			
Value factor	0.38	2.75	0.14	0.08	-0.27		
Size factor	0.20	2.95	0.07	-0.22	0.28	-0.21	
Momentum factor	0.73	4.06	0.12	0.15	-0.13	-0.17	-0.03

Table V
Robustness of Labor Market Tightness Portfolios

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 of year T and are held from July of year T to June of year $T + 1$. In Panel B, firms are assigned into deciles at the end of every month τ and are held during month $\tau + 2$. In Panel C, firms are assigned into deciles at the end of every month τ and are held without rebalancing for 12 month beginning in month $\tau + 3$. In Panel D, firms are assigned into quintiles rather than deciles. In Panel E, firms below 20th percentile of NYSE market capitalization are excluded from the sample. In Panel F, labor market tightness factor is defined as the residual from a time-series regression of ϑ defined in equation (2) on change in industrial production, change in consumer price index, dividend yield, T-bill rate, term spread, and default spread. In Panel G, labor market tightness factor is defined as the residual from fitting log of labor market tightness to an ARMA(1,1) model. In Panel H, regression (3) is amended to also include size, value, and momentum factors. Conditional alphas are intercepts from regression $R_{j,t} - R_{f,t} = \alpha_j + \beta_j [1 \ Z_{t-1}]' (R_{M,t} - R_{f,t}) + e_{j,t}$, 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. Ferson and Schadt (FS) conditional alpha is computed using as instruments demeaned dividend yield, term spread, T-bill rate, and default spread. Boguth, Carlson, Fisher, and Simutin (BCFS) 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. In all panels, portfolios are initially value-weighted. The sample period is 1954-2012.

Decile	Raw	Unconditional Alphas			Cond Alphas		4-Factor Loadings			
	Return	CAPM	3-Factor	4-Factor	FS	BCFS	MKT	HML	SMB	UMD
A. Non-overlapping portfolios										
Low-High	0.55	0.59	0.51	0.47	0.50	0.50	0.01	0.24	-0.25	0.04
t-statistic	[3.42]	[3.68]	[3.19]	[2.89]	[3.16]	[3.11]	[0.29]	[3.92]	[-4.50]	[0.94]
B. One-month holding										
Low-High	0.51	0.58	0.61	0.46	0.54	0.52	-0.06	0.04	-0.28	0.16
t-statistic	[2.99]	[3.44]	[3.63]	[2.67]	[3.35]	[3.23]	[-1.42]	[0.67]	[-4.84]	[3.85]
C. Two-months waiting										
Low-High	0.47	0.52	0.52	0.42	0.48	0.47	-0.02	0.07	-0.24	0.11
t-statistic	[3.49]	[3.84]	[3.90]	[3.08]	[3.62]	[3.52]	[-0.58]	[1.35]	[-5.17]	[3.23]
D. Quintile portfolios										
Low-High	0.32	0.39	0.39	0.30	0.35	0.32	-0.06	0.07	-0.19	0.09
t-statistic	[2.82]	[3.44]	[3.44]	[2.60]	[3.13]	[2.90]	[-2.29]	[1.61]	[-4.91]	[3.33]
E. Excluding micro caps										
Low-High	0.45	0.49	0.51	0.35	0.49	0.46	-0.05	0.01	-0.01	0.17
t-statistic	[3.72]	[4.05]	[4.15]	[2.84]	[4.08]	[3.88]	[-1.79]	[0.31]	[-0.22]	[5.54]
F. Alternative definition 1 of ϑ										
Low-High	0.44	0.48	0.50	0.46	0.47	0.46	-0.04	0.02	-0.19	0.04
t-statistic	[3.22]	[3.55]	[3.65]	[3.32]	[3.53]	[3.46]	[-1.30]	[0.44]	[-4.08]	[1.06]
G. Alternative definition 2 of ϑ										
Low-High	0.45	0.51	0.49	0.41	0.45	0.44	-0.03	0.11	-0.24	0.09
t-statistic	[3.28]	[3.68]	[3.58]	[2.87]	[3.29]	[3.20]	[-0.80]	[2.13]	[-4.92]	[2.70]
H. Alternative computation of β^θ										
Low-High	0.29	0.36	0.38	0.30	0.32	0.31	-0.08	0.03	-0.08	0.20
t-statistic	[2.36]	[2.90]	[3.04]	[2.55]	[2.62]	[2.54]	[-2.55]	[0.70]	[-1.82]	[6.46]

Table VI
Fama-MacBeth Regressions of Annual Stock Returns

This table reports the results of annual Fama-MacBeth regressions. Stock returns from July of year T to June of year $T + 1$ are regressed on β^θ , loading on the labor market tightness factor measured as of the end of May of year T ; β^M , market beta measured as of the same time; ME, log of market equity measured as of the end of June of year T ; BM, log of the ratio of book equity to market equity measured following Davis, Fama, and French (2000); RU, 12-month stock return ending in June of year T ; and HN, IK, and AG, the new hiring, investment, and asset growth rates, respectively, defined as in Belo, Lin, and Bazdresch (2013). Reported are average coefficients and the corresponding Newey and West (1987) t -statistics. Details of variable definitions are in Appendix A. The sample period is 1954-2012.

Reg	β^θ	β^M	ME	BM	RU	HN	IK	AG
(1)	-0.028 [-2.46]	0.000 [-0.01]	-0.015 [-2.70]					
(2)	-0.030 [-2.30]	0.009 [0.67]	-0.011 [-1.95]	0.035 [4.20]				
(3)	-0.040 [-2.85]	0.010 [0.72]	-0.012 [-2.22]	0.037 [4.65]	0.066 [3.46]			
(4)	-0.043 [-3.01]	0.010 [0.72]	-0.012 [-2.29]	0.032 [4.09]	0.067 [3.38]	-0.050 [-3.48]		
(5)	-0.048 [-2.94]	0.011 [0.78]	-0.013 [-2.30]	0.033 [4.37]	0.066 [3.32]		-0.017 [-1.54]	
(6)	-0.040 [-2.75]	0.012 [0.83]	-0.011 [-2.13]	0.032 [4.10]	0.066 [3.36]			-0.075 [-5.02]
(7)	-0.046 [-3.01]	0.011 [0.77]	-0.012 [-2.25]	0.028 [3.67]	0.068 [3.36]	0.004 [0.26]	0.014 [1.16]	-0.091 [-4.66]

Table VII
Performance of Labor Market Tightness Portfolios: Industry-Level Analysis

This table reports in Panel A average raw returns and alphas, in percent per month, and loadings from the four-factor model regressions for the ten portfolios of stocks sorted within each of the 48 Ken French-defined industries on the basis of their loadings on the labor market tightness factor. Each of the ten portfolios thus has similar industry composition. Panel B repeats the analysis for the ten portfolios obtained by sorting 48 value-weighted industry portfolios from Ken French's data library on the basis of their loadings on the labor market tightness factor. The table also shows returns, alphas, and loadings for the portfolio that is long the low decile and short the high group. The bottom row of each panel gives t -statistics for the low-high portfolio. Firms (in Panel A) or industries (in Panel B) are assigned into deciles at the end of every month τ and are held without rebalancing for twelve months beginning in month $\tau + 2$. Conditional alphas are intercepts from regression $R_{j,t} - R_{f,t} = \alpha_j + \beta_j [1 \ Z_{t-1}]' (R_{M,t} - R_{f,t}) + e_{j,\tau}$, 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. Ferson and Schadt (FS) conditional alpha is computed using as instruments demeaned dividend yield, term spread, T-bill rate, and default spread. Boguth, Carlson, Fisher, and Simutin (BCFS) 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. The sample period is 1954-2012.

Decile	Raw	Unconditional Alphas			Cond. Alphas		4-Factor Loadings			
	Return	CAPM	3-Factor	4-Factor	FS	BCFS	MKT	HML	SMB	UMD
A. Portfolios of Stocks Sorted by Labor Market Tightness Loadings Within Industries										
Low	1.10	0.09	0.04	0.02	0.10	0.09	1.10	0.06	0.20	0.03
2	1.06	0.10	0.06	0.07	0.09	0.09	1.03	0.06	0.06	-0.01
3	1.01	0.08	0.07	0.11	0.07	0.07	0.99	0.01	-0.05	-0.04
4	0.99	0.08	0.07	0.08	0.06	0.07	0.97	0.03	-0.07	-0.01
5	0.97	0.06	0.06	0.07	0.04	0.04	0.98	0.03	-0.12	-0.02
6	0.99	0.08	0.08	0.08	0.06	0.05	0.98	0.02	-0.12	0.00
7	0.93	0.01	0.00	0.00	-0.01	-0.01	0.99	0.03	-0.08	0.00
8	0.92	-0.01	-0.03	-0.03	-0.01	-0.01	1.00	0.05	-0.05	0.00
9	0.91	-0.06	-0.09	-0.06	-0.04	-0.03	1.05	0.05	0.04	-0.04
High	0.73	-0.27	-0.34	-0.31	-0.25	-0.25	1.08	0.09	0.27	-0.03
Low-High	0.37	0.36	0.39	0.33	0.35	0.34	0.02	-0.03	-0.07	0.06
t -statistic	[3.84]	[3.76]	[4.01]	[3.36]	[3.79]	[3.63]	[0.96]	[-0.78]	[-1.98]	[2.40]
B. Portfolios of Industries Sorted by Labor Market Tightness Loadings										
Low	1.30	0.34	0.23	0.13	0.29	0.27	1.03	0.22	0.25	0.11
2	1.14	0.19	0.10	0.10	0.15	0.14	1.00	0.16	0.16	0.01
3	1.13	0.18	0.08	0.07	0.15	0.14	1.00	0.16	0.21	0.02
4	1.11	0.17	0.08	0.05	0.14	0.13	0.99	0.17	0.23	0.03
5	1.08	0.13	0.04	0.05	0.11	0.10	1.00	0.14	0.20	-0.01
6	1.05	0.09	0.00	0.04	0.06	0.06	1.03	0.14	0.17	-0.04
7	1.04	0.07	-0.03	0.01	0.03	0.03	1.03	0.16	0.18	-0.04
8	1.09	0.12	0.00	0.05	0.06	0.06	1.05	0.19	0.17	-0.06
9	0.90	-0.08	-0.21	-0.11	-0.15	-0.14	1.05	0.19	0.21	-0.11
High	0.96	-0.03	-0.16	-0.13	-0.09	-0.10	1.05	0.19	0.32	-0.03
Low-High	0.34	0.37	0.39	0.26	0.38	0.37	-0.02	0.03	-0.07	0.13
t -statistic	[2.37]	[2.55]	[2.60]	[1.71]	[2.54]	[2.45]	[-0.48]	[0.56]	[-1.41]	[3.67]

Table VIII
Benchmark Parameter Calibration

This table lists the parameter values of the benchmark calibration. The model is based on a monthly frequency.

Parameter	Symbol	Value
<i>Labor Market</i>		
Workers quit rate	s	0.022
Matching function elasticity	ξ	1.27
Bargaining power of worker	η	0.1
Benefit of being unemployed	b	0.75
Returns to scale of labor	α	0.75
Flow cost of vacancy posting	κ_h	0.4
Flow cost of firing	κ_f	0.2
Fixed operating costs	f_0	0.13
Proportional operating costs	f_1	0.045
<i>Shocks</i>		
Persistence of aggregate productivity shock	ρ_x	$0.95^{1/3}$
Cond. volatility of aggregate productivity shock	σ_x	0.005
Persistence of matching efficiency shock	ρ_p	$0.88^{1/3}$
Cond. volatility of matching efficiency shock	σ_p	0.025
Persistence of idiosyncratic productivity shock	ρ_z	0.96
Cond. volatility of idiosyncratic productivity shock	σ_z	0.072
<i>Pricing Kernel</i>		
Time discount rate	β	0.9935
Price of risk of aggregate productivity shock	γ_x	1
Price of risk of matching efficiency shock	$\gamma_{p,0}$	-5
Sensitivity of matching efficiency shock	$\gamma_{p,1}$	5
Interest rate sensitivity	ϕ	-0.0225

Table IX
Aggregate and Firm-specific Target Moments

This table summarizes the empirical aggregate and firm-specific moments used to calibrate model parameters.

Moment	Data	Model
<i>Aggregate Labor Market</i>		
Unemployment rate	0.058	0.058
Hiring rate	0.035	0.035
Layoff rate	0.014	0.013
Labor market tightness	0.634	0.635
Volatility of labor market tightness factor	0.055	0.053
Labor share of income	0.717	0.706
Volatility of aggregate wages to aggregate output	0.520	0.517
Aggregate profits to aggregate output	0.110	0.110
<i>Firm-Level Employment</i>		
Volatility of annual employment growth rates	0.236	0.219
Skewness of annual employment growth rates	0.123	0.140
Fraction of firms with zero annual employment growth rates	0.097	0.077
<i>Asset Prices</i>		
Average risk-free rate	0.010	0.010
Volatility of risk-free rate	0.021	0.021
Average market return	0.081	0.088
Stock market volatility	0.176	0.174

Table X
Portfolio Returns of the Benchmark Model

This table compares our benchmark model performance with data. All numbers are expressed in percentage terms. Return refers to future portfolio equity return. Under benchmark calibration, we simulate panels of firms and compute their theoretical loadings on the labor market tightness factor. We sort portfolios according to their LMT loadings and calculate the realized and expected future annualized equity returns. The benchmark model produces monotonically decreasing portfolio returns, which resembles the data.

Decile	Data			Model		
	β_θ	Return	α_{CAPM}	β_θ	Return	α_{CAPM}
Low	-0.74	1.10	0.09	-0.84	1.09	0.23
2	-0.39	1.06	0.10	-0.64	1.02	0.19
3	-0.23	1.01	0.08	-0.48	0.99	0.16
4	-0.12	0.99	0.08	-0.39	0.96	0.15
5	-0.03	0.97	0.06	-0.23	0.91	0.13
6	0.06	0.99	0.08	-0.18	0.92	0.12
7	0.16	0.93	0.01	0.00	0.86	0.00
8	0.28	0.92	-0.01	0.08	0.85	-0.01
9	0.45	0.91	-0.06	0.29	0.79	-0.04
High	0.85	0.73	-0.27	0.61	0.73	-0.08
Low-High	-1.59	0.37	0.36	-1.45	0.36	0.31

Table XI
Portfolio Returns across Alternative Calibrations

This table compares the model-simulated expected future equity returns of 10 portfolios sorted by the loadings on labor market tightness factor across alternative calibrations. Benchmark stands for the benchmark labor capital asset pricing model that we propose in this paper. In the comparative statics experiments, Model (1) - (2) change the pricing kernel; Model (3) - (4) change the shock process; Model (5) - (9) change the parameters or model related to the labor market. In Model (1), we assume that matching efficiency shocks are not priced, $\gamma_{p,0} = 0$, and raise the price of productivity shocks to 10, $\gamma_x = 10$. In Model (2), we set $\gamma_{p,1} = 0$, so that the aggregate p shock has constant price of risk. The cross-sectional spread becomes 0.22. In Model (3) - (4), p shock and x shock are turned off respectively. In Model (5), we set $\theta_t = \theta_{ss}$ in the wage process so that the wage rate does not depend on the labor market equilibrium. In Model (6), we increase the firm's bargaining power to $\eta = 0.5$ and adjust the labor force scaler to match unemployment rate at 5.8%. In Model (7), we set $\kappa_f = 0$ so that there is zero cost to downsize. In Model (8), we reduces κ_h from 0.4 to 0.3 and adjust the labor force scaler to match unemployment rate at 5.8%. In Model (9), we remove the fixed operation cost $f_0 = 0$.

Decile	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low	0.89	1.00	0.86	1.08	1.13	0.99	1.05	1.06	0.94
2	0.91	0.97	0.87	1.03	1.10	0.96	1.00	1.01	0.92
3	0.91	0.95	0.85	1.00	1.08	0.94	0.96	0.97	0.91
4	0.93	0.94	0.87	0.98	1.05	0.94	0.95	0.95	0.90
5	0.93	0.91	0.87	0.94	1.03	0.91	0.90	0.91	0.88
6	0.94	0.91	0.87	0.94	0.99	0.91	0.90	0.91	0.88
7	0.97	0.88	0.88	0.89	0.96	0.88	0.86	0.86	0.86
8	0.97	0.87	0.87	0.88	0.93	0.88	0.84	0.85	0.85
9	0.96	0.84	0.86	0.83	0.85	0.85	0.80	0.80	0.83
High	0.98	0.78	0.88	0.77	0.69	0.80	0.74	0.74	0.79
Low-High	-0.09	0.22	-0.02	0.31	0.44	0.18	0.31	0.32	0.15