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 based on their 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 labor force participation rate. Firms with low factor loadings are not hedged against adverse labor force shocks and thus 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, however, are very costly for firms because they need to spend time and resources to search for new employees.[1]

Building on the seminal contributions of Diamond (1982), Mortensen (1972, 1982), and Pissarides (1985, 2000), we show that labor search frictions are an important determinant of the cross-section of equity returns.[2] In search models, firms post vacancies looking for workers, and unemployed workers search 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 ratio of vacant positions to unemployed workers. This ratio is usually referred to as *labor market tightness* and is the key variable of our analysis.

We begin by studying the empirical relation between labor market conditions and the cross section of equity returns. To construct aggregate labor market tightness, we compute the ratio of the monthly vacancy index from the Conference Board to the unemployed population. Rather than using the unemployment rate as a proxy for the unemployed population,[3] we normalize employment by the total population, thereby correcting for time variation in the labor force participation rate as reported by the Bureau of Labor Statistics. Consistent with the empirical exercise, shocks to the labor force participation rate are a key driver of the model.

To measure the sensitivity of firm value to labor market conditions, we estimate loadings of equity returns with respect to log changes in labor market tightness controlling for the

[1]These search costs arise because of heterogeneity among workers and jobs and information imperfections. Davis, Faberman, and Haltiwanger (2006) document that the average duration for a job position being vacant ranges from 14 to 25 days. "According 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." (Advance Online)

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

[3]See for instance Shimer (2005) and Hornstein, Krusell, and Violantel (2005).

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 US stock returns over the 1954 to 2009 period, we show that the loadings on the 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. This difference cannot be explained by commonly considered asset pricing models, for example, the Fama and French (1993) three-factor model.

Portfolio sorts are potentially problematic as such univariate analysis fails to account for other firm characteristics that have been shown to relate to future returns. To ensure that the relation between labor search frictions and future stock returns is not attributable to such characteristics, we also run Fama and MacBeth (1973) regressions of annual stock returns on the 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 new hiring rates of Bazdresch, Belo, and Lin (2012).

The Fama-MacBeth analysis confirms the robustness of results obtained in simple portfolio sorts. The coefficients of 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 1.4%.

To interpret the empirical findings, we propose a labor augmented capital asset pricing model. We build a partial equilibrium labor market model and study its implications for firm employment policies and stock returns. For tractability we do not model the supply of labor as optimal households decisions, instead we assume an exogenous pricing kernel. Our model features a cross section of firms with heterogeneity in their idiosyncratic shocks and employment levels, extending the representative firm framework in Pissarides (1985) and Mortensen and Pissarides (1994). 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 our model, the fraction of successfully filled vacancies depends on labor market tightness which results from the aggregation of firms vacancy policies. As such, equilibrium in the labor market requires that firm hiring policies are consistent with the implied labor market tightness. This imperfect labor market matching creates rents in equilibrium which are shared between each firm and its workforce according to a collective 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 mass of workers which we interpret as labor market participation shock. A positive labor market participation shock reduces the congestion of the labor market as there are more unemployed workers looking for jobs. As a result, posting vacancies to hire workers becomes more attractive for firms.

Quantitatively, our model replicates the negative relation between loadings on labor market tightness and future returns. As an equilibrium outcome of the labor market, labor market tightness is negatively related to labor market participation shocks. Consequently, firms with low labor market tightness loadings are very sensitive to labor market conditions arising from labor force participation shocks. After an adverse labor force participation shock, these firms face higher average recruiting costs as the labor market becomes more congested. As a result, these firms are riskier and require higher risk premia as their cash flows are not hedged against adverse labor force shocks.

To solve the model numerically we follow the idea of approximate aggregation introduced in Krusell and Smith (1998). We approximate the firm level distribution with labor market tightness which is a sufficient statistic to solve the firm's problem. Its dynamics are approximated with a log-linear functional form. The application of Krusell and Smith (1998) here differs from Zhang (2005) in an important way. Zhang (2005) assumes that firms can perfectly forecast the next period's industry equilibrium given the current information set. In contrast, we assume that future labor market tightness is stochastic and firms form rational expectations about it. This modeling assumption is consistent with our empirical evidence that stock return loadings with respect to labor market tightness affect valuations.

Our paper builds on the production based asset pricing literature started by Cochrane (1991) and Jermann (1998). Pioneered by Berk, Green, and Naik (1999), there exists now a large literature studying cross sectional asset pricing implications of firm real investment decisions, for instance, 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 (2012a,b) who highlight that investment specific shocks are related to firm risk premia. We differ by studying frictions on the labor market and specifically shocks to the labor force.

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). Along this line, there also exist recent papers linking 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 coming from rigid wages, Donangelo (2012) focuses on labor mobilities, Eisfeldt and Papanikolaou (2012) study organizational capital embedded in specialized labor input, and Bazdresch, Belo, and Lin (2012) analyze convex labor adjustment costs. We differ by exploring the impact of search costs on cross sectional asset prices.

II. Empirical Results

In this section, we document a robust negative relation between the stock return correlations with changes in labor market conditions and future equity returns. We establish this result by studying portfolios sorted by loadings on the labor market tightness factor and confirm it using Fama and 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 based on portfolio sorts to the 1954-2009 period. Fama-MacBeth regressions additionally require Compustat data on book equity and other firm attributes, and consequently analysis based on those data is conducted for the 1960-2009 sample. In the Appendix 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 rate 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 unemployment rate and labor force participation rate (LFPR). Hence labor market tightness is given by

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

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). We define the labor market tightness factor in month t as the change in logs of this ratio:

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

The time series properties of ϑ_t, its components and other macro variables are summarized in Table 1. Despite being a highly procyclical factor, ϑ_t does not strongly comove with other monthly macro factors that are known to have non-zero prices of risk, such as dividend yield, term spread, default spread, change in the consumer price index, and change in industrial production.

[4] The 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.

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

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

where $R_{f,t}$ is the risk-free rate of return, and $R_{i,t}$ and $R_{M,t}$ are stock i and market excess returns in month $t \in \{\tau - 35, \tau\}$. Figure 2 plots the time series of cross-sectional average, median, and other percentiles of the loadings on the labor market tightness factor, highlighting wide cross-sectional differences in the computed loadings. We now turn to exploring whether these loadings have significant predictive power for stock returns.

C. Evidence from Portfolio Sorts

At the end of each month τ, we rank stocks into deciles on the basis of loadings on the labor market tightness factor $\beta^{\theta}_{i,\tau}$ 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 2 presents average firm characteristics of the resulting decile portfolios. No strong relation emerges between loadings on the labor market tightness factor and any of the considered characteristics. Firms in the high decile are on average somewhat smaller than those in the low group, but the relation is not monotonic. Median characteristics are qualitatively similar to the reported averages and are omitted for brevity.

For each decile portfolio, we obtain monthly time series of returns from January 1954 until December 2009. Table 3 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 3 also shows loadings on market, value, size, and momentum factors of each group. Firms in the high decile have somewhat larger size betas and lower value and momentum loadings. To account for differences in risk across the deciles, we also present alphas from market, Fama and French (1993), and Carhart (1997) models.

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, 1.14% monthly, whereas the high beta group performs most poorly, generating on average just 0.64% per month. The difference in performance of the two deciles, at 0.50%, is economically large and statistically significant (t-statistic of 3.60). The corresponding differences in alphas are similarly striking, ranging from 0.43% (t-statistic of 3.06) for Carhart four-factor alphas to 0.55% (t-statistic of 3.95) for market model alphas.

Results of portfolio sorts thus strongly suggest that the 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 3 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 4 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 less volatile than the market or the momentum factors (see also Panel B of Figure 3) and achieves a Sharpe ratio (0.14) comparable to that of the value factor.

D. Evidence from Portfolio Sorts: Robustness

We now demonstrate robustness of the relation between stock return loadings on changes in labor market tightness and future equity returns to considering alternative portfolio formation approaches, excluding micro cap stocks, and using a modified definition of labor market tightness factor. Table 5 summarizes the results of the robustness tests.

Portfolio formation design employed in the previous section is motivated by investment strategies such as momentum studied 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 5 show that each of these approaches results in even more dramatic difference in future performance of low and high β^{θ} deciles. For example, the difference in average returns of the low and high groups reaches 0.62% monthly when portfolios are formed once a year, compared to 0.50% reported in Table 3.

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 3 are obtained assuming a one-month interval to ensure that all the variables needed to compute labor market tightness (vacancy index, unemployment rate, and labor force participation rate) are publicly available. 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 period. Panel C of Table 5 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 0.49% per month.

Panel D of Table 5 shows that the results are also robust to excluding microcaps, which we define to include 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 impact the results.[5]

We also consider robustness to an alternative definition of labor market tightness factor. Table 1 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

[5] Untabulated results also confirm robustness of the results to imposing a minimum price filter and to excluding Nasdaq-listed stocks.

variables, we define labor market tightness as the residual $\tilde{\vartheta}_t$ from a time series regression

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

where IP_t, CPI_t, DY_t, TB_t, TS_t, and DS_t are changes in industrial production, consumer price index, dividend yield, T-bill rate, term spread, and default spread, respectively. The disadvantage of this approach is that it introduces a look-ahead bias as the regression coefficients are estimated using the entire sample. Yet, it allows us to focus on the component of labor market tightness that is unrelated to other macro variables that can have non-zero prices of risk. Panel E of Table 5 shows that our results are little affected by the change 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 meaningful, ranging between 0.42% and 0.46% monthly.

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 A1 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. Evidence from 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, $\beta^{\theta}_{i,\tau}$, and subsequent equity returns. However, such univariate analysis does not account for other firm characteristics that have been shown to relate to future returns. In this section, 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 determine whether the ability of $\beta^{\theta}_{i,\tau}$ to forecast returns is subsumed by other firm characteristics. To this end, we perform annual Fama-MacBeth (1973) regressions

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

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 variables 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 Bazdresch, Belo, and Lin (2012). We winsorize all independent variables cross-sectionally at 1% and 99%.

Table 6 summarizes the results of Fama-MacBeth regressions. The coefficient on β^{θ} is negative and statistically significant in each considered specification, even after accounting for other cross-sectional predictors of equity returns. These results confirm the negative relation between loadings on the labor market tightness factor and future stock returns documented in Table 3. 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 deciles portfolios are 3.7 standard deviations apart, suggesting that the difference in future stock returns of the two groups exceeds 5%, in line with the results presented in Table 3.

The labor market tightness factor is highly correlated with its components and with changes in industrial production (see Table 1). 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 rate, or industrial production, respectively. These loadings are estimated in the same manner as 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 A2 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. Evidence from Two-Pass Regressions on Industry Portfolio Returns

Motivated by the empirical evidence of a strong negative relation between individual stocks' loadings on the labor market tightness factor and future equity returns, we now turn to examining the pricing implications of labor market tightness cross-sectionally using 48 industry portfolios.[6] We perform the analysis in two stages. In the first stage, we regress monthly excess returns of each industry i on market excess returns, labor market tightness factor, and (depending on specification) on size, value, and momentum factors:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i^M (R_{M,t} - R_{f,t}) + \beta_i^\theta \vartheta_t + \beta_i^{HML} HML_t + \beta_i^{SMB} SMB_t + \beta_i^{UMD} UMD_t + \varepsilon_{i,t},$$

In the second stage, we run a cross-sectional regression of industry returns on the loadings estimated in the first stage. Table 7 summarizes the results of the second-stage regressions. Each considered specification shows a significantly negative price of risk for the labor market tightness factor, corroborating our previous findings of a strong negative relation between loadings on the labor market tightness factor and future stock performance. We now turn to understanding this empirical relation by formalizing a model of labor market frictions.

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

[6] We obtain industry returns from Ken French's website.

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

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

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

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

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

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.

Firm's labor capital is determined in a Kydland and Prescott (1982) 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 given period. Instead, the probability q that vacancies are filled is endogenously determined in equilibrium and depends on the congestion of the labor market denoted by θ_t. Once workers and firms are randomly matched, workers either quit voluntarily at a constant rate of s or are fired endogenously by the firm, denoted by $F_{i,t}$. Taken together, this implies the following law of motion for the firm level employment size

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

B. Labor Market 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

$$\bar{V}_t = \int V_{i,t} d\mu_t, \tag{9}$$

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.

An important feature of our model is the size of the aggregate labor force. It is commonly assumed in the literature a constant unit mass of workers (e.g. Diamond (1982), Merz (1995), Shimer (2005)). We instead model the mass of the labor force as stochastic with unit mean. The time varying size of the labor force captures the notion that the participation in the work force is not constant over time. For instance, discouraged people stop searching for jobs or the baby boomer generation enters the labor force.

The labor force is defined as the sum of employed and unemployed. Thus, the total number of unemployed equals

$$\bar{U}_t = e^{p_t} - \int N_{i,t} d\mu_t, \tag{10}$$

where e^{p_t} is the size of labor force, and p_t denotes an exogenous labor market participation shock. This shock 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

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

In the model, we treat the population as constant. The labor market participation shock therefore corresponds to the ratio of labor force to population, i.e., the labor force participation rate as reported by the Bureau of Labor Statistics.

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

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

and the probability for a vacancy to be filled per unit of time can be computed from

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

This probability 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.

C. Nash Bargaining Wages

Wages are determined as the outcome of collective Nash bargaining between each firm and its workforce. Workers have bargaining weight $\eta \in (0, 1)$. If they decide not to work they receive unemployment benefit b which represents the value of their outside option. Let κ_h be the unit cost of vacancy posting. Workers are also rewarded the saving of hiring costs ($\kappa_h \theta_t$) that firms enjoy when a job position is filled. When markets are tighter, workers can thus extract higher wages from the firm.

The firm with employment size $N_{i,t}$ benefits from hiring the marginal worker through an increase in output by the marginal product of labor, $\alpha e^{x_t + z_{i,t}} N_{i,t}^{\alpha-1}$. Similar to Stole and Zwiebel (1996) on wage bargaining in multi-worker firms, collective Nash bargaining and worker homogeneity imply that each worker receives the average marginal product of labor, $Y_{i,t}/N_{i,t}$. The overall wage rate is then given by[7]

$$w_{i,t} = \eta(Y_{i,t}/N_{i,t} + \kappa_h \theta_t) + (1 - \eta)b. \tag{14}$$

D. Firm Value

We do not model the supply side of labor coming form households. This would require to solve a full general equilibrium model. Instead, following Berk, Green, and Naik (1999) and Lettau and Wachter (2011), we specify an exogenous pricing kernel

$$M_{t+1} = e^{-r_{f,t}} \frac{\exp(-\gamma_x x_{t+1} - \gamma_p p_{t+1})}{\mathbb{E}_t[\exp(-\gamma_x x_{t+1} - \gamma_p p_{t+1})]} \tag{15}$$

We assume that both the aggregate productivity shock x_t and labor force participation shock p_t are priced with their respective market prices of risk γ_x and γ_p. The pricing kernel (15) implies that $r_{f,t}$ is the log risk-free rate which follows an affine process as a function of the aggregate shocks

$$r_{f,t} = \bar{r}_f + B(x_t + p_t). \tag{16}$$

[7] See the Appendix for a detailed derivation.

implying an average risk-free rate of $\bar{r}_f$ with variance $B^2(\sigma_p^2/(1-\rho_p^2)+\sigma_x^2/(1-\rho_x^2))$.

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. The firm's Bellman equation is

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

subject to equations (4) - (14) where $D_{i,t}$ denotes dividends given by

$$D_{i,t} = Y_{i,t} - w_{i,t}N_{i,t} - \kappa_h V_{i,t} - \kappa_f F_{i,t}. \tag{18}$$

Notice that the firm's problem is well-defined given labor market tightness θ_t and an expectation about how it evolves. Given optimal firm value $S_{i,t}$, stock returns are defined as

$$R_{i,t+1} = \frac{S_{i,t+1}}{S_{i,t} - D_{i,t}}. \tag{19}$$

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. 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,

$$\mu_{t+1} = \Gamma(\mu_t, x_t, p_t). \tag{20}$$

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

$$\theta_t = \frac{\int V(\Omega_{i,t})d\mu_t}{e^{p_t} - \int N_{i,t}d\mu_t}. \tag{21}$$

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 (15), Nash bargaining wage rate (14), and labor market tightness θ_t, $V(\Omega_{i,t})$ and $F(\Omega_{i,t})$ solve the firm's Bellman equation (17) where $S(\Omega_{i,t})$ is its solution.

- Consistency: θ_t is consistent with the labor market equilibrium (21), 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 (17) 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 (20), we assume a log-linear functional form

$$\log\theta_{t+1} = \tau_0 + \tau_\theta \log\theta_t + \tau_{x,0}x_t + \tau_{p,0}p_t + \tau_{x,1}x_{t+1} + \tau_{p,1}p_{t+1}. \tag{22}$$

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

$$\vartheta_{t+1} = \tau_0 + (\tau_\theta - 1)\log\theta_t + \tau_{x,0}x_t + \tau_{p,0}p_t + \tau_{x,1}x_{t+1} + \tau_{p,1}p_{t+1}. \tag{23}$$

Our application of Krusell and Smith (1998) differs from Zhang (2005) along several dimensions. First, θ_{t+1} is a function of firm distribution at time $t+1$ and hence is not in the information set of date t. The forecasting rule (22) at time t does not enable firms to learn θ_{t+1} exactly, 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. Second, at each period of the simulation, we impose labor market equilibrium by solving θ_t

as the fixed point in Equation (21). Hence, there is no discrepancy between the forecasted θ_{t+1} and the realized θ_{t+1}. Third, the use of θ_t as the sufficient statistic of firm distribution is consistent with the empirical findings that firms' stock return sensitivity to changes in θ_t is relevant for their valuation.

G. Expected Returns and the Labor Capital Asset Pricing Model

Given the pricing kernel (15), expected excess returns satisfy the Euler equation $\mathbb{E}_t[M_{t+1}R^e_{i,t+1}] = 0$. In order to derive a linear pricing relation, we apply a log linear approximation to the pricing kernel implying[8]

$$\mathbb{E}_t[R^e_{i,t+1}] \approx \beta^x_{i,t}\lambda^x_t + \beta^p_{i,t}\lambda^p_t$$

where $\beta^x_{i,t}$ and $\beta^p_{i,t}$ are loadings on aggregate productivity and labor force participations shocks and λ^x_t and λ^p_t are their respective factor risk premia.

Since aggregate productivity is not directly observable in the data, we also approximate the return on the market as an affine function of the aggregate shocks

$$R^e_{M,t+1} = \nu_0 + \nu_\theta \log\theta_t + \nu_{x,0}x_t + \nu_{p,0}p_t + \nu_{x,1}x_{t+1} + \nu_{p,1}p_{t+1}. \tag{24}$$

As a result, expected excess returns obey a two factor structure in the market return and labor market tightness

$$\mathbb{E}_t[R^e_{i,t+1}] \approx \beta^M_{i,t}\lambda_{t,M} + \beta^\theta_{i,t}\lambda_{t,\theta}, \tag{25}$$

where $\beta^M_{i,t}$ and $\beta^\theta_{i,t}$ are the loadings on the market return and log-changes of labor market tightness and $\lambda_{t,M}$ and $\lambda_{t,\theta}$ are the respective factor risk premia given by

$$\lambda^M_t = \nu_x\lambda^x_t + \nu_p\lambda^p_t \qquad \lambda^\theta_t = \tau_x\lambda^x_t + \tau_p\lambda^p_t$$

We call relation (25) the Labor Capital Asset Pricing Model.

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

[8] See the appendix for a detailed derivation.

tightness and show that the model is consistent with the inverse relationship 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 detail in Appendix C. Given the equilibrium forecasting rule, firms make optimal employment policies. We simulate panels with 5000 firms for 5300 periods.

A. Calibration

This section describes how we calibrate the parameter values and simulate the model. We adopt a monthly frequency because labor market and equity market data are available at that frequency. Table (8) summarizes the parameter calibration of the benchmark model.

Since labor is the only input into production, the aggregate productivity shock process is calibrated to the nonfarm business labor productivity index (output per hour) reported by the BLS. We calculate the percentage deviations from the Hodrick-Prescott filtered trend for quarterly labor productivity and fit an AR(1) process to estimate the persistence parameter and conditional standard deviation. Then we transform the quarterly estimates to monthly frequency according to Heer and Mauner (2011) to get $\rho_x = 0.9830$ and $\sigma_x = 0.007$. Regarding the shock to the labor force participation, we take the time series of monthly labor force participation rates from the BLS and normalize it to have unit mean. Then we fit an AR(1) process to the log of the normalized time series and estimate the persistence $\rho_p = 0.9967$, and conditional standard deviation $\sigma_p = 0.0033$. Notice that the correlation of the two shock series estimated from data is only 0.019, which justifies our model assumption that the two aggregate shocks are independent.

The average risk-free rate $\bar{r}_f = 0.005$ is set according to the monthly risk-free rate. The affine structure coefficient B governs how the risk-free rate moves with the aggregate shocks. It is chosen such that the risk-free rate is countercyclical and has an annual standard deviation of 2.26%. The prices of risk of the aggregate shocks γ_x and γ_p are set to match the average market excess return and the Sharpe ratio. We assume that the aggregate productivity shock

x and labor force participation shock p both have positive price of risk. Berk, Green, and Naik (1999) and Zhang (2005) provide a motivation for $\gamma_x > 0$ in an economy with only x shocks.

The assumption of $\gamma_p > 0$ can be motivated as follows. In general equilibrium economy with a representative household, labor market participation is an endogenous outcome determined as a consumption and leisure tradeoff where participation means a reduction in leisure. Eckstein and Wolpin (1989) and Schirle (2008) show that endogenous variation in participation can be linked to preference shocks. Under these assumption, the substitution effect between consumption and leisure dominates in equilibrium, implying that consumption and leisure are negatively correlated. This positive comovement between consumption and participation indicates that, in a model with exogenous shocks to participation, these shocks should display a positive price of risk.

The labor literature provides several empirical studies to calibrate the labor market parameters. According to Davis, Faberman, and Haltiwanger (2012), the monthly total separation rate measured in the Job Openings and Labor Turnover Survey (JOLTS) is 0.034. In JOLTS, each establishment reports employment hires, quits, and layoffs separately, which allows us to differentiate between voluntary quits and involuntary layoffs. In both den Haan, Ramey, and Watson (2000) and Davis, Faberman, and Haltiwanger (2012), the average level of quits are twice that of layoffs. As such, we set the monthly exogenous quit rate $s = 0.023$.

Shimer (2005) measures the aggregate monthly job finding rate $f(\theta) = 0.45$ and the average vacancy filling rate $q(\theta) = 0.71$. Given these estimates, the curvature of the matching function has $\xi = 1.28$ coming from the steady state relation $q = \left((f/q)^{\xi} + 1\right)^{-1/\xi}$.

The remaining parameters are chosen to match the simulated moments. Table (9) summarizes the selected target moments from data and the simulated moments under the benchmark calibration. The curvature of the production function α is set to match the average monthly unemployment rate which is 5.7% in the data as reported by the BLS.

The level of unemployment benefit b relates to the average labor share of income measured as total compensation of employees divided by output. Using data from The National Income and Product Accounts (NIPA), Gomme and Greenwood (1995) and Gomme and Rupert (2007) report 0.717 for this moment.

The bargaining power of workers η determines the rigidity of wages. On the simulated panel, for each firm we calculate the ratio of the standard deviation of log-changes of firm-specific wage rate to the standard deviation of log-changes of firm output. Then we average over all the firms to match the data moment as in Gourio (2007). We also calculate the standard deviation of log-changes of aggregate after-tax profit to that of total output, and match it to Gourio (2007).

The cost parameters κ_h and κ_f determine both the overall costs of adjusting the workforce as well as the behavior of firm policies. Specifically, we determine the average total adjustment costs to total output, which Yashiv (2011) empirically estimates to be are around 2% of output. The proportional cost structure also implies the existence of firms that are neither posting vacancies nor laying off workers. The average percentage of Compustat firms with zero net annual employment growth rate during 1980-2010 is 7.04%. We refer to this as average inaction fraction. On the simulated panel of firms, we average the monthly firm employment growth rate across 12 months to get the annual average for each firm every year. Then we compute the percentage of firms with absolute annual employment adjustment rate less than 1% to match the inaction fraction.[9]

The persistence and volatility of firm idiosyncratic shock process correspond to the cross-sectional dispersion and persistence of firm-level employment growth rate. We obtain the average dispersion of annual employment growth rates 0.25 by taking the cross-sectional standard deviation of firm level employment growth rate for each year, and take the average of the time series ranging 1980-2010 in Compustat. The corresponding moment is calculated the same way in simulations to match the data. To measure the persistence and volatility of labor adjustment, Davis, Haltiwanger, Jarmin, Miranda, Foote, and Nagypal (2006) adopt a moving average formula and obtain the average volatility of annual employment growth rates 0.2 for Compustat firms. We follow their exact procedure on simulated data.

[9] We use the 1% to allow for numerical errors in the simulation, and measurement errors in the data.

B. Equilibrium Forecasting Rules

Table 10 shows the coefficient estimates for the equilibrium forecasting rule of labor market tightness using the benchmark calibration. With this forecasting rule, we solve the model, and simulate a panel of firms and estimate ex post the affine structure for market excess returns, (24).

In the model, labor market tightness is autocorrelated, positively related to aggregate productivity and negatively to the labor force participation. An increase in aggregate productivity leads to more vacancy postings by firms because of an increase in the marginal product of labor and a decrease in discount rates. More vacant positions means tighter labor markets and a drop in matching probabilities. The direction of labor force participation shock on labor market tightness is not obvious because both the numerator and the denominator of labor market tightness (see Equation (21)) increase upon an increase in p_t. Given our calibration, the second channel dominates in the competitive labor market equilibrium and θ_t decreases endogenously with the participation shock.

Figure 4 illustrates this endogenous link. In a model without a labor market equilibrium, p shocks only enter θ_t through the denominator. When there is an increase in p from p_0 to p_1, we move along the black solid curve from point A to B. Accounting for the firms' endogenous response, an increase in p_t affects the pricing kernel and firms' expectation about θ_t and thus vacancy postings $V(\Omega_{i,t})$ increase. This endogenous response shifts the curve outward, and we end up with the equilibrium at C. We also emphasize that when γ_p is large enough, the endogenous increase in vacancies could be so strong that the curve shifts more outward to the dashed red line with equilibrium D. Consequently, endogenous firm behavior also imposes a constraint on our calibration.

The realized market excess return is mainly driven by the innovations of the two aggregate shocks and not by lagged labor market tightness. When favorable aggregate shocks hit the economy, prices increase and the realized market excess return is positive. As such, the regression coefficients show that both $\nu_{x,1} > 0$ and $\nu_{p,1} > 0$. We use this information to compute theoretical loadings on labor market tightness controlling for the market excess return.

C. Cross Section of Equity Returns

Following the empirical procedure in Section II, we calculate loadings $\beta^{\theta}_{i,t}$ on the θ factor of each stock i controlling for the market excess return. We emphasize that in the data, we calculate the loadings $\beta^{\theta}_{i,t}$ using a two-factor model of market excess return and labor market tightness, see Equation (3). In the model, since we know the theoretical conditional distribution of both the technology shock and the labor market participation shock, we can calculate the theoretical loadings implied by the equilibrium law (24).

To assess to what extent our model can explain the empirically observed negative relationship between labor market tightness factor loadings and future stock returns, we use the simulated data and sort portfolios into portfolios according to their factor loadings. For the benchmark results, we use a monthly rebalancing procedure, sort the simulated 5000 firms into ten portfolios, and calculate value weighted average returns for each portfolio. Table 11 compares the simulated return spread with the data.

In the model, the annualized average return difference between the low and heigh loading portfolio is 4.3% relative to 6.0% in the data. Our results are robust with respect to portfolios held and rebalanced at different horizons. Table 12 shows the simulated portfolio spread from the benchmark model with portfolio rebalanced after one month, two months, four months, six months, and 12 months. The portfolio spread decreases slightly as we increase the rebalancing horizon, because as noise increases month after month, the predictability becomes weaker. However, at a one year rebalancing horizon, the return spread is still significant.

What is economic mechanism underlying our model? Due to the proportional hiring and firing costs, the optimal firm policy exhibits stylized (s, S) patterns in adjusting employment size and thus regions of inactivity. Figure 5 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 line is the optimal policy in the benchmark model. It displays two kinks. In the 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 the labor force participation, ideally, firms would like to hire only when the labor market is not tight. Yet, the (s, S) firm policy arising from proportional hiring and firing costs prevents some firms form doing so. When the economy is hit by an adverse p shock, equilibrium θ goes up. Hiring becomes relatively more costly and thus less attractive to firms. Some firms which are not in the inaction region have to incur relatively higher cost in refilling their lost workers. Hence they end up with lower cash flows. When a positive p shock realizes, firms wish to hire by taking advantage of the favorable labor market condition. Some firms that have hired enough when p was low, are now in the constrained inaction region. Firms with these characteristics have positively correlated cash flows with p shocks and thus they are very sensitive to the labor market conditions. Consequently, they are not hedged against the risk from labor market, are riskier and require higher expected return. Empirically, these firms have low loadings on labor market tightness. Figure 6 illustrates the inverse relationship between expected returns and loadings on labor market tightness in the cross section.

Selecting firms based on loadings on labor market conditions is informative about future returns whereas sorts based on hiring characteristics are not. 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.

Table 13 compares different model versions. The benchmark model generates the negative relation between loadings on labor market tightness and future returns as in the data. The portfolio spread in the data amounts to 6% annually. The benchmark model generates 4.34%, which is a large portion of the empirical cross sectional return spread.

In Model 1, we do not solve for a labor market equilibrium. Instead, firms believe that labor market tightness is constant in expectations, $\theta_t = \theta^{ss}$. Without the equilibrium law of motion for θ_t, we calculate loadings on ϑ by rolling regressions on realized ϑ. In a model without labor market equilibrium, the loadings on labor market tightness are not directly linked to firm value but are still correlated with loadings on aggregate shocks. As a result, the model fails short to explain the data.

Model 2 is only driven by aggregate productivity shocks and Model 3 only by labor force participation shocks. In a setting with only aggregate productivity shocks (Model 2), the price of θ risk is positive because labor market tightness and aggregate productivity are positively related. As a result, we obtain a negative return difference for the low minus high portfolio, the opposite of what we observe in the data. Contrary, in a model of only labor force participation shocks (Model 3), we still see a negative price of risk for the θ factor in equilibrium.

V. Conclusion

This paper analyzes the cross sectional asset pricing implications of a risk factor originating in the labor market. In the data, we first document a robust negative relation between stock return loadings on changes in labor market tightness and future stock returns in the cross section. We also show that a labor capital asset pricing model with heterogeneous firms making dynamic employment decisions under labor search frictions can replicate the empirical facts.

We add the following novel features to the standard labor search model: (1) Equilibrium labor market tightness is determined endogenously as the total number of optimal vacancy posted over the total unemployed and hence depends on the time-varying firm level distribution. (2) Rather than holding the the labor force constant, we model the mass of the labor force as stochastic, which is motivated by the fluctuations in the labor force participation rate. As an equilibrium outcome, labor market tightness is negatively related with participation shocks. Consequently, firms with low labor market tightness loadings are very sensitive to labor market conditions that originate from labor force participation shocks. These firms have cash flows which are not hedged against adverse labor force 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 list Compustat data items 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 Bazdresch, Belo, and Lin (2012) 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 Bazdresch, Belo, and Lin (2012) 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).

B. Wage Process

In this section, we derive the Nash bargaining wage equation, following the logic in Kuehn, Petrosky-Nadeau, and Zhang (2012). First we reduce the firms problem (17), with the law of motion of employment size (8) to the following:

$$S_{i,t} = \max_{V_{i,t} \geq 0} \{Y_{i,t} - w_{i,t}N_{i,t} - \kappa_h V_{i,t} + \mathbb{E}_t \left[M_{t+1}S_{i,t+1}\right],$$

subject to $N_{i,t+1} = (1-s)N_{i,t} + q(\theta_t)V_{i,t}$.

We justify the rational of reducing the endogenous firing $F_{i,t}$ at the end of this section. Denote the marginal value of a vacancy posting for a firm with state variables $\Omega_{i,t}$ as $S_{V_{i,t}}$. Take the first order condition with respect to $N_{i,t+1}$, we get that at the optimum, firms set the marginal value of vacancy posting equal to zero, i.e.

$$S_{V_{i,t}} = -\frac{\kappa_h}{q(\theta_t)} + \lambda_{i,t} + \mathbb{E}_t \left[M_{t+1}S_{N_{i,t+1}}\right] = 0. \tag{26}$$

Denote the marginal value of an employment worker to a firm with state variable $\Omega_{i,t}$ as $S_{N_{i,t}}$. Then by definition,

$$S_{N_{i,t}} = \frac{\partial Y_{i,t}}{\partial N_{i,t}} - w_{i,t} + (1-s)\mathbb{E}_t \left[M_{t+1}S_{N_{i,t+1}}\right]. \tag{27}$$

In order to perform Nash bargaining over the total surplus of a match, we need to specify the marginal gains of an employed and an unemployed worker. Since we do not model the household size, let's 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 $J_{N_{i,t}}$ as the marginal utility of an employed worker to the representative family, and $J_{V_{i,t}}$ as the marginal value of an unemployed worker to the family. Given that an employed worker receives $w_{i,t}$ for period t, and has probability s of being separated from the job next period, we can write out the following recursive form for $J_{N_{i,t}}$as

$$\frac{J_{N_{i,t}}}{\phi_t} = w_{i,t} + \mathbb{E}_t \left[M_{t+1}\left((1-s)\frac{J_{N_{i,t+1}}}{\phi_{t+1}} + s\frac{J_{U_{i,t+1}}}{\phi_{t+1}}\right)\right] \tag{28}$$

Similarly, an unemployed worker receives the unemployment benefit b for the current period, and has a probability $f(\theta_t)$ of finding a job next period. We can write the following recursive form for $J_{U_{i,t}}$ as

$$\frac{J_{U_{i,t}}}{\phi_t} = b + \mathbb{E}_t \left[M_{t+1} \left(f(\theta_t) \frac{J_{N_{i,t+1}}}{\phi_{t+1}} + (1 - f(\theta_t)) \frac{J_{U_{i,t+1}}}{\phi_{t+1}} \right) \right]. \tag{29}$$

The marginal worker and the firm bargain over the total surplus of a match $\Lambda_t \equiv \frac{J_{N_{i,t}} - J_{U_{i,t}}}{\phi_t} + S_{N_{i,t}} - S_{V_{i,t}}$. Given worker's bargaining power η, Nash bargaining solves the following problem

$$\max_{\{w_{i,t}\}} \left(\frac{J_{N_{i,t}} - J_{U_{i,t}}}{\phi_t} \right)^{\eta} (S_{N_{i,t}} - S_{V_{i,t}})^{1-\eta}.$$

The Nash bargaining solution features

$$\frac{J_{N_{i,t}} - J_{U_{i,t}}}{\phi_t} = \eta \left(\frac{J_{N_{i,t}} - J_{U_{i,t}}}{\phi_t} + S_{N_{i,t}} - S_{V_{i,t}} \right). \tag{30}$$

Combining (26), (27), (28), (29),

$$\Lambda_t \equiv \frac{J_{N_{i,t}} - J_{U_{i,t}}}{\phi_t} + S_{N_{i,t}} - S_{V_{i,t}} = w_{i,t} - b + \mathbb{E}_t \left[M_{t+1}(1 - s - f(\theta_t)) \frac{J_{N_{i,t+1}} - J_{U_{i,t+1}}}{\phi_{t+1}} \right] + \frac{\partial Y_{i,t}}{\partial N_{i,t}} - w_{i,t} + (1-s)\mathbb{E}_t[M_{t+1} S_{N_{i,t+1}}],$$

plugging in (30), we further have

$$\Lambda_t = \frac{\partial Y_{i,t}}{\partial N_{i,t}} - b + (1-s)\mathbb{E}_t[M_{t+1}\Lambda_{t+1}] - \eta f(\theta_t)\mathbb{E}_t[M_{t+1}\Lambda_{t+1}]. \tag{31}$$

Now rewrite (27) in terms of Λ_t

$$(1-\eta)\Lambda_t = \frac{\partial Y_{i,t}}{\partial N_{i,t}} - w_{i,t} + (1-s)(1-\eta)\mathbb{E}_t[M_{t+1}\Lambda_{t+1}]. \tag{32}$$

Combining (31) and (32), $w_{i,t} = \eta \frac{\partial Y_{i,t}}{\partial N_{i,t}} + (1-\eta)b + (1-\eta)\eta f(\theta_t)\mathbb{E}_t[M_{t+1}\Lambda_{t+1}] = \eta \frac{\partial Y_{i,t}}{\partial N_{i,t}} + (1-\eta)b + \eta f(\theta_t)\mathbb{E}_t[M_{t+1}S_{N_{i,t+1}}] = \eta \left(\frac{\partial Y_{i,t}}{\partial N_{i,t}} + \theta_t \kappa_h \right) + (1-\eta)b - \eta f(\theta_t)\lambda_{i,t}$, where the last step is obtained by realizing (27), and $\theta_t = \frac{f(\theta_t)}{q(\theta_t)}$.

Based on this wage equation that is obtained by Nash bargaining between the firm with employment size $N_{i,t}$ and the marginal worker, we now generalize it to collective Nash bargaining [10] at period t, between the firm with employment size $N_{i,t}$, and its entire workforce,

[10] This idea originates from Stole and Zwiebel (1996). In their setting with multiple homogeneous workers with non-constant marginal product, wage is allowed to be renegotiated every period conditional on the states. If we assume individual bargaining rather than the collective setting, then the marginal impact of losing this one marginal worker is not just revenue decreases by $\frac{\partial Y_{i,t}}{\partial N_{i,t}}$, but also the wage rate of the rest of the workers are renegotiated. In a discrete setting with n denoting the total number of workers, the marginal wage rate of worker n, $w(n)$ is a function of MP_n and $w(n-1)$; and $w(n-1)$ is a function of MP_{n-1} and $w(n-2)$, and so on. Substituting recursively, $w(n)$ is a function of MP_n, MP_{n-1}, MP_{n-2}, ... MP_1, which boils down the idea of collective bargaining between the firm and its workforce as a whole.

visualized as a labor union of a firm. All the above derivations remain except that the marginal product, or the contribution to the firm's profit by the entire workforce of the firm is $Y_{i,t} = \int_0^{N_{i,t}} \alpha e^{x_t+z_{i,t}} n^{\alpha-1} dn$. Since workers are homogeneous in our setting, they divide equally their bargaining outcome, implying an overall wage rate $w_{i,t} = \eta\left(\frac{Y_{i,t}}{N_{i,t}} + \kappa_h\theta_t\right) + (1-\eta)b - \eta f(\theta_t)\lambda_{i,t}$. Recall that $\lambda_{i,t}$ is the Lagrange multiplier of the vacancy posting non-negativity constraints at the margin. If marginally, a firm is not posting any vacancy, i.e. $V_{i,t} = 0$, and $\lambda_{i,t} > 0$, hence $w_{i,t} < \eta\left(\frac{Y_{i,t}}{N_{i,t}} + \kappa_h\theta_t\right) + (1-\eta)b$. However, since we assume collective bargaining between the firm and its entire workforce, the vacancy posting decision at the margin when the entire workforce wants to quit must be such that $V_{i,t} > 0$. Since $V_{i,t}F_{i,t} = 0$, we hence justify that the endogenous firing decision can be omitted when deriving the Nash bargaining wage rate. Hence the overall wage rate is shown to be

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

C. The Labor CAPM

A log linear approximation of the pricing kernel (15) is given by

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

implying

$$\begin{aligned} \mathbb{E}_t[R^e_{i,t+1}] &= -\text{Cov}_t\left(\frac{M_{t+1}}{\mathbb{E}_t[M_{t+1}]}, R_{i,t+1}\right) \\ &\approx -\text{Cov}_t(m_{t+1}, R_{t+1}) \\ &= \gamma_x \text{Cov}_t(x_{t+1}, R_{i,t+1}) + \gamma_p \text{Cov}_t(p_{t+1}, R_{i,t+1}) \\ &= \beta^x_{i,t}\lambda^x_t + \beta^p_{i,t}\lambda^p_t \end{aligned} \tag{33}$$

where risk loadings are given by

$$\beta^x_{i,t} = \frac{\text{Cov}_t(x_{t+1}, R_{i,t+1})}{\text{Var}_t(x_{t+1})} \qquad \beta^p_{i,t} = \frac{\text{Cov}_t(p_{t+1}, R_{i,t+1})}{\text{Var}_t(p_{t+1})}$$

and factor risk premia are

$$\lambda^x_t = \gamma_x \text{Var}_t(x_{t+1}) \qquad \lambda^p_t = \gamma_p \text{Var}_t(p_{t+1})$$

We also approximate the return on the market as an affine function of the aggregate shocks (24). Given (23) and (24), we can show that

$$\begin{aligned}
\mathbb{E}_t[R^e_{i,t+1}] &= \gamma_M \mathrm{Cov}_t(R_{M,t+1}, R_{i,t+1}) + \gamma_\theta \mathrm{Cov}_t(\vartheta_{t+1}, R_{i,t+1}) \\
&= \gamma_M \mathrm{Cov}_t(\nu_x x_{t+1} + \nu_p p_{t+1}, R_{i,t+1}) + \gamma_\theta \mathrm{Cov}_t(\tau_x x_{t+1} + \tau_p p_{t+1}, R_{i,t+1}) \\
&= (\gamma_M \nu_x + \gamma_\theta \tau_x)\mathrm{Cov}_t(x_{t+1}, R_{i,t+1}) + (\gamma_\theta \tau_p + \gamma_M \nu_p)\mathrm{Cov}_t(p_{t+1}, R_{i,t+1}). \quad (34)
\end{aligned}$$

Thus, by matching coefficient of (33) and (34)

$$\gamma_x = \gamma_M \nu_x + \gamma_\theta \tau_x \qquad \gamma_p = \gamma_\theta \tau_p + \gamma_M \nu_p$$

Multivariate loadings with respect to labor market tightness and the market return satisfy

$$\begin{aligned}
\beta^\theta_{i,t} &= \frac{\nu_p}{\tau_x \nu_p - \nu_x \tau_p}\beta^x_{i,t} - \frac{\nu_x}{\tau_x \nu_p - \nu_x \tau_p}\beta^p_{i,t} \\
\beta^M_{i,t} &= \frac{-\tau_p}{\tau_x \nu_p - \nu_x \tau_p}\beta^x_{i,t} + \frac{\tau_x}{\tau_x \nu_p - \nu_x \tau_p}\beta^p_{i,t}
\end{aligned}$$

Note, that these loadings are not univariate regression betas because the market return and labor market tightness are correlated.

Given the two-factor specification (34), its beta representation yields the labor CAPM (25) defined as

$$\mathbb{E}_t[R^e_{i,t+1}] = \beta^M_{i,t}\lambda^M_t + \beta^\theta_{i,t}\lambda^\theta_t$$

where factor risk premia are

$$\lambda^M_t = \nu_x \lambda^x_t + \nu_p \lambda^p_t \qquad \lambda^\theta_t = \tau_x \lambda^x_t + \tau_p \lambda^p_t$$

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 ($n_x = 5$), 11 for z ($n_z = 11$) and 5 for p ($n_p = 5$). 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 simulation[11]. The space of the labor market tightness θ needs

[11] In 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.

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 with more numbers of the grid points, and non-evenly spaced grids, 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 (22). 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 (17) given the forecasting rule coefficients τ. For this step we use value function iteration. Specifically, the firm value function solves

$$S(N, z, x, p, \theta) = \max\{S(N, z, x, p, \theta)^h, S(N, z, x, p, \theta)^f\}, \tag{35}$$

where

$$\begin{aligned} S(N, z, x, p, \theta)^h = & \max_{N' \geq (1-s)N} \{(1 - \eta)e^{x+z}N^\alpha - [\eta\kappa_h\theta + (1 - \eta)b]N- \\ & \frac{\kappa_h}{q(\theta)}[N' - (1 - s)N] + \mathbb{E}[M'S(N', z', x', p', \theta')|z, N, x, p, \theta]\}, \end{aligned} \tag{36}$$

and

$$\begin{aligned} S(N, z, x, p, \theta)^f = & \max_{N' \leq (1-s)N} \{(1 - \eta)e^{x+z}N^\alpha - [\eta\kappa_h\theta + (1 - \eta)b]N- \\ & \kappa_f[(1-)N - N'] + \mathbb{E}[M'S(N', z', x', p', \theta')|z, N, x, p, \theta]\}. \end{aligned} \tag{37}$$

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 (21). 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.

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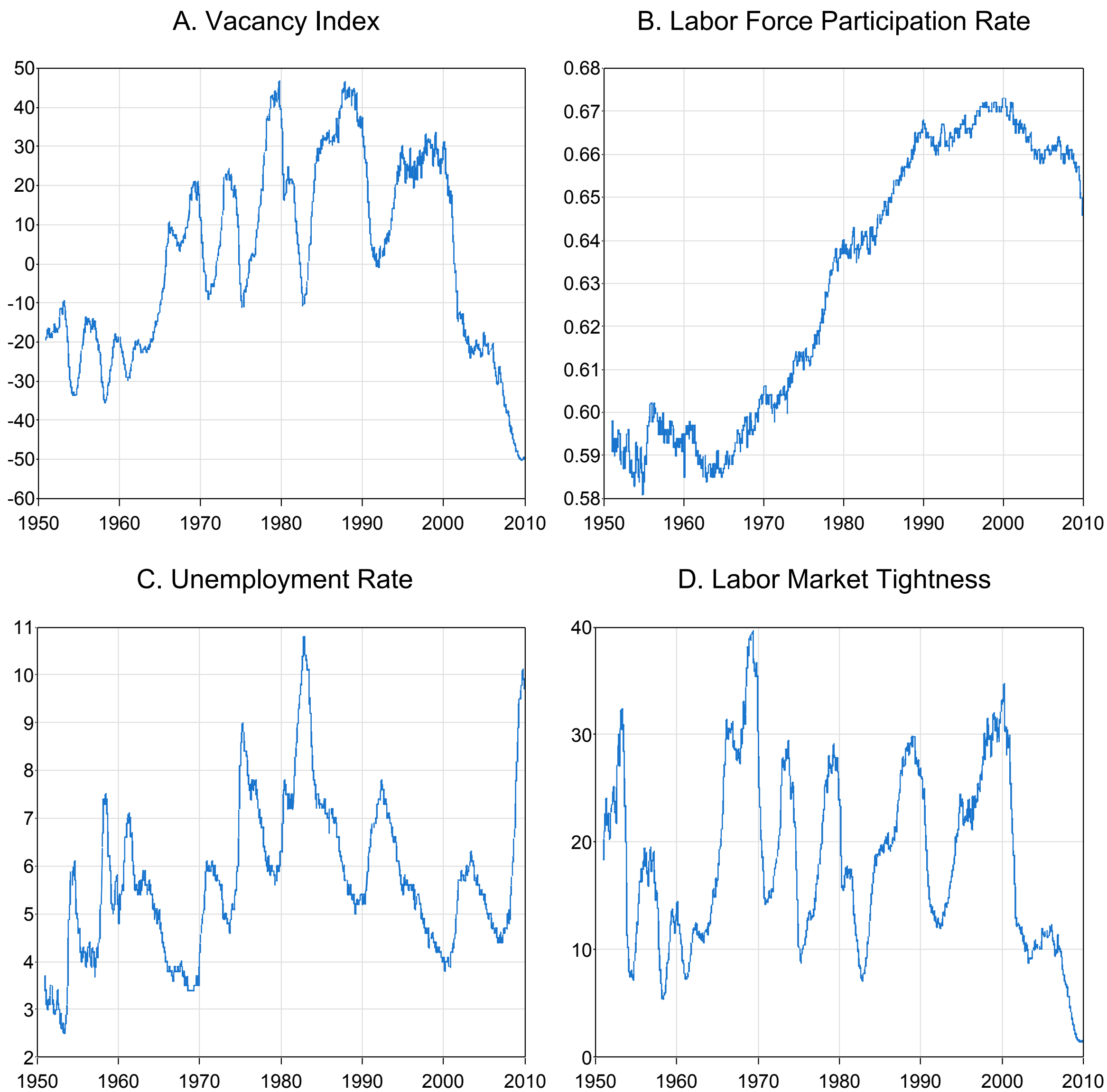

Figure 1. Labor Market Tightness and Its Components. This figure plots the monthly time series of the vacancy index (normalized to have average of one), the labor force participation rate, the unemployment rate, and the labor market tightness.

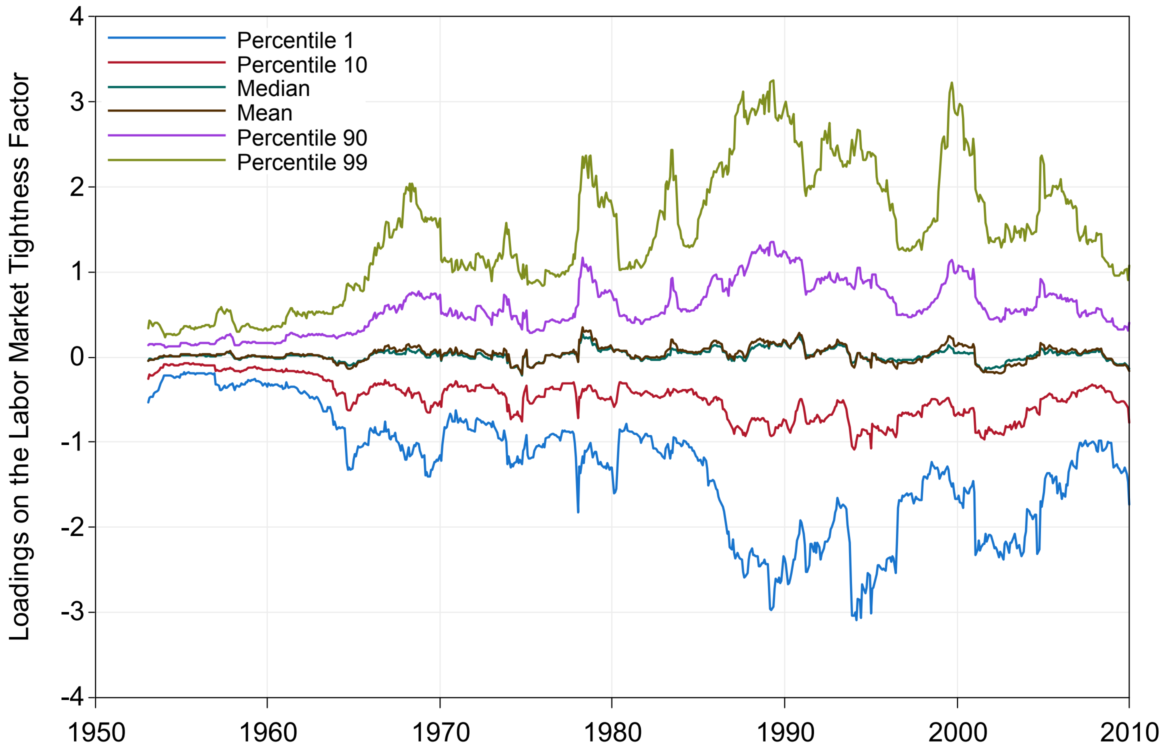

Figure 2. Loadings on the Labor Market Tightness Factor. This figure plots time series statistics of the loadings of common stocks on the labor market tightness factor.

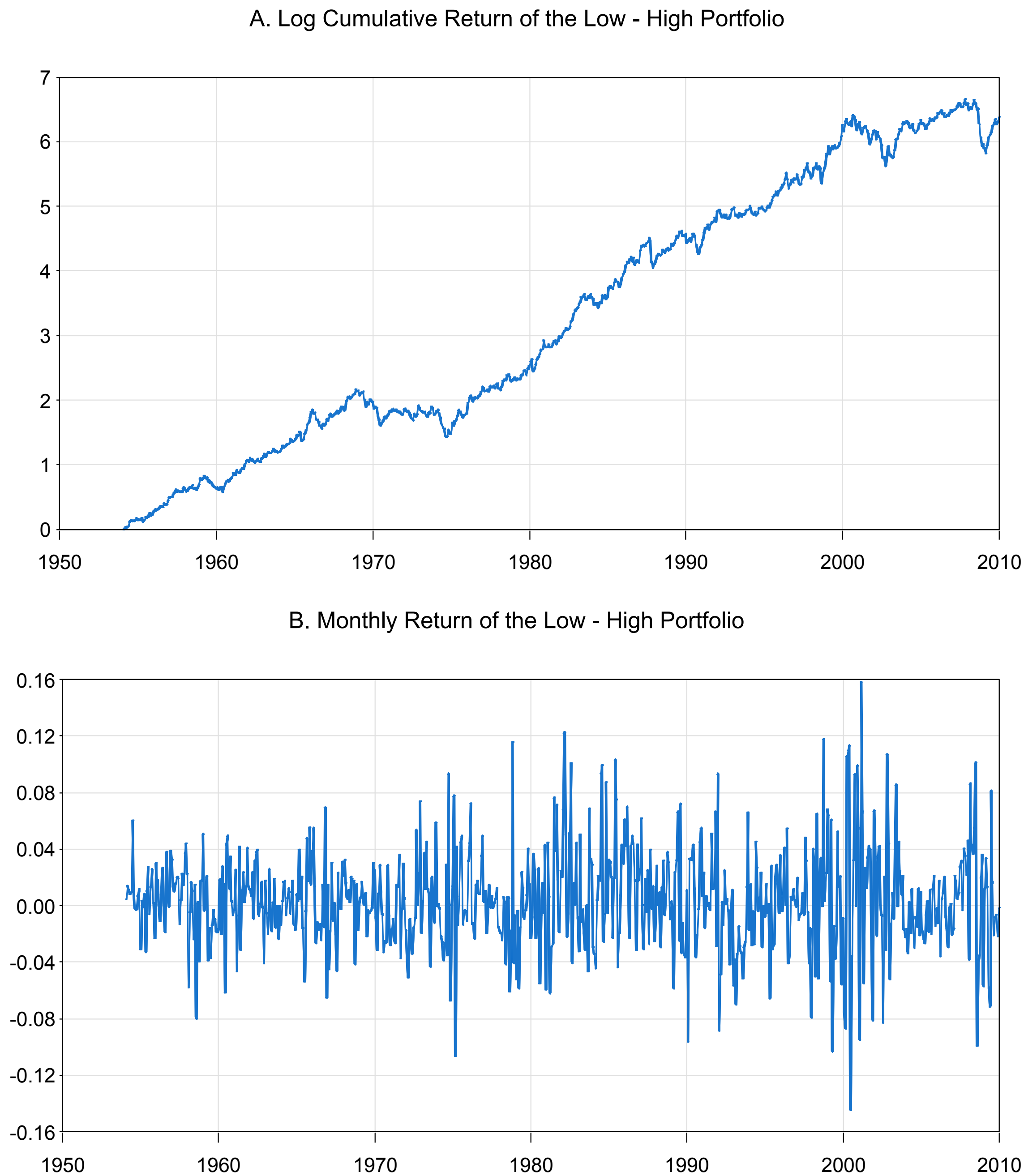

Figure 3. Returns of the Low - High Portfolio. This figure plots in Panel A the log cumulative return of the portfolio that longs the decile of stocks with the lowest exposure to the labor market tightness factor and shorts the decile of stocks with the highest loadings and shows in Panel B the monthly returns of this portfolio.

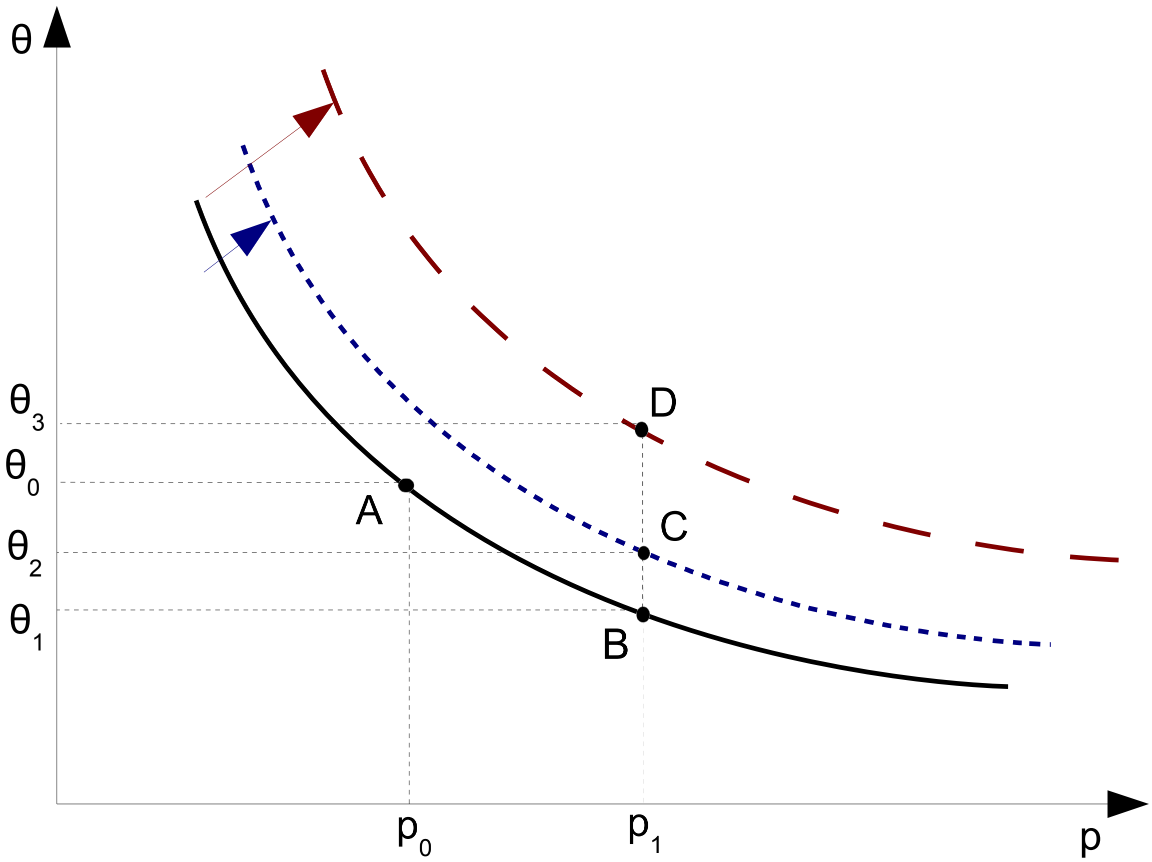

Figure 4. Equilibrium Labor Market Tightness vs. Participation Shock This figure illustrates the endogenous relationship between the equilibrium labor market tightness and the participation shock. From p_0 to p_1, without endogenous response from firm vacancy posting, equilibrium θ goes from A to B. Point C indicates the equilibrium endogenous response of θ when accounting for the endogenous firm vacancy postings. D illustrates an overreact of the endogenous response.

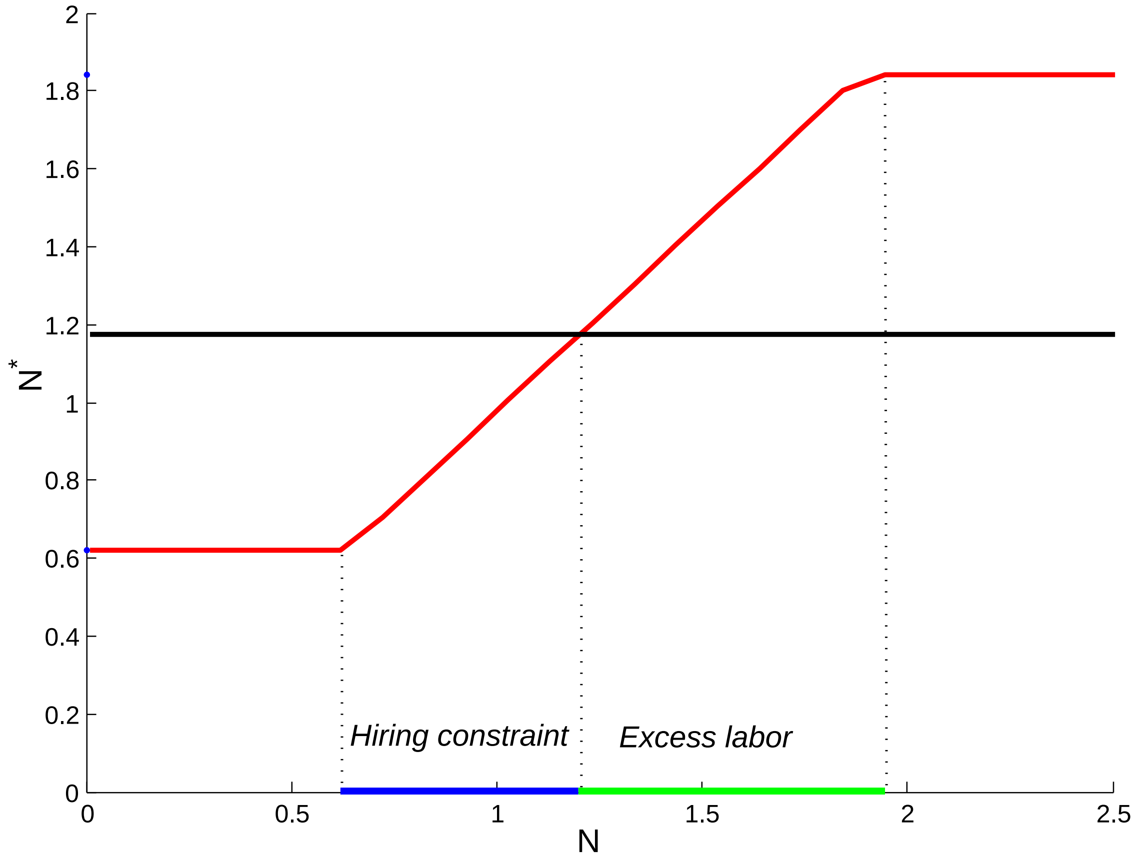

Figure 5. Firm Optimal Employment Policy with Search Frictions This figure demonstrates the firm optimal labor adjustment policy under search frictions. Take an individual firm with states (x, p, θ, z), point N_* is the optimal future employment level in a frictionless environment, and the solid red curve N^* depicts optimal policy with search frictions. The region *Hiring constraint* are firms who wish to, but cannot refill their lost workers. The region *Excess labor* are 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.

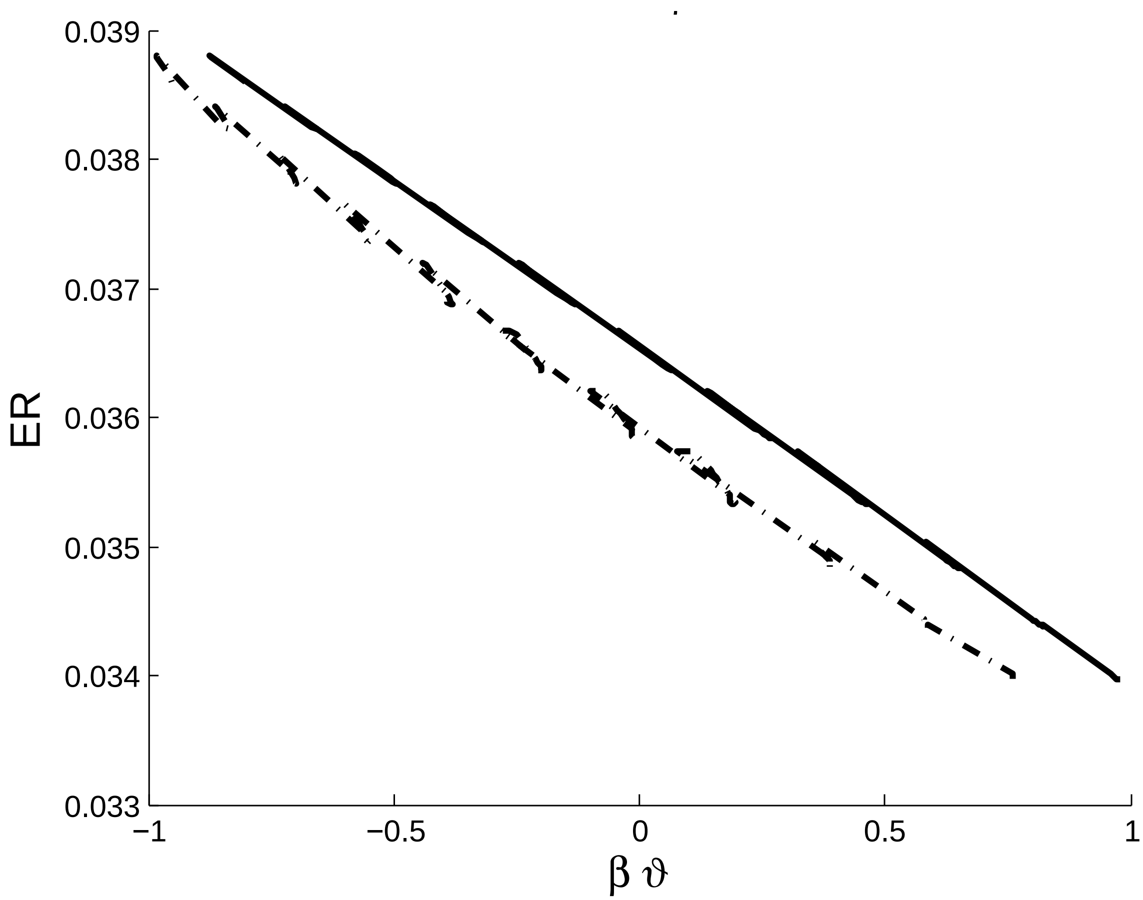

Figure 6. Expected Future Return vs. Loading on ϑ: on the Grid This figure shows at equilibrium, the inverse cross-sectional relationship between the expected future equity returns and the loadings on log-changes of labor market tightness, controlling for market excess return. We compute the factor loadings and expected equity returns theoretically on the grid, and show the cross-sectional scatter plot, conditional on two randomly picked aggregate states (x, p, θ).

Table 1. Summary Statistics

	Mean	Standard Deviation	Correlations ϑ	VAC	UNEMP	LFPR	IP	CPI	DY	TB	TS
ϑ	-0.0030	0.0567									
VAC	-0.0011	0.0346	0.8232								
UNEMP	0.0017	0.0340	-0.8249	-0.3623							
LFPR	0.0002	0.0030	-0.1166	0.0398	0.1474						
IP	0.0024	0.0091	0.5590	0.4504	-0.4798	0.0475					
CPI	0.0031	0.0032	-0.0662	-0.0445	0.0611	0.0509	-0.0736				
DY	0.0324	0.0113	-0.0672	-0.0020	0.1117	0.0650	-0.0970	0.3359			
TB	0.0041	0.0024	-0.0744	-0.0810	0.0373	0.0384	-0.0836	0.5295	0.4757		
TS	0.0140	0.0120	0.0853	0.0983	-0.0432	-0.0244	0.0309	-0.2864	-0.0725	-0.3487	
DS	0.0098	0.0046	-0.2579	-0.2056	0.2225	-0.0310	-0.2877	0.1146	0.3481	0.3573	0.3004

Notes: This table reports summary statistics for the monthly labor market tightness, change in the vacancy index, change in the unemployment rate, change in the labor force participation rate, change in the industrial production, change in the consumer price index, dividend yield, T-bill rate, term spread, and default spread (ϑ, VAC, UNEMP, LFPR, IP, CPI, DY, TB, TS, and DS, respectively) calculated for the 1954-2009 period.

Table 2. Characteristics of β^θ Decile Portfolios

Decile	β^θ	β^M	BM	ME	RU	AG	IK	HN	Div	Div Vol
Low β^θ	-0.8474	1.3672	0.8816	4.7924	0.1721	0.1419	0.3358	0.0676	0.0235	0.0208
2	-0.4054	1.1752	0.9099	5.7850	0.1511	0.1436	0.3060	0.0828	0.0325	0.0176
3	-0.2373	1.0915	0.9048	6.0958	0.1293	0.1190	0.2815	0.0593	0.0357	0.0163
4	-0.1212	1.0272	0.9155	6.3182	0.1370	0.1218	0.2773	0.0716	0.0373	0.0155
5	-0.0241	1.0184	0.9325	6.2076	0.1363	0.1226	0.2669	0.0556	0.0368	0.0150
6	0.0701	1.0262	0.9326	6.0468	0.1320	0.1238	0.2709	0.0556	0.0347	0.0150
7	0.1737	1.0602	0.9336	5.8670	0.1335	0.1219	0.2810	0.0641	0.0339	0.0152
8	0.3018	1.1156	0.9358	5.5260	0.1363	0.1262	0.2943	0.0638	0.0311	0.0146
9	0.4928	1.1988	0.9144	4.9682	0.1351	0.1339	0.3075	0.0801	0.0255	0.0144
High β^θ	0.9944	1.3812	0.8721	3.9462	0.1517	0.1432	0.3497	0.0805	0.0113	0.0241

Notes: This table reports average characteristics for the ten portfolios of stocks sorted on the basis of 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; AG, IK, and HN are the asset growth, investment, and new hiring rates, respectively; Div is dividend yield. Mean characteristics are calculated in each annual cross-section and then averaged. Dividend volatility reported in the last column is computed at the portfolio level as the volatility of the difference of portfolio returns with and without dividends.

Table 3. FUTURE PERFORMANCE AND RISK LOADINGS OF PORTFOLIOS SORTED BY LOADINGS ON LABOR MARKET TIGHTNESS FACTOR

	Raw	Alphas			Loadings from 4-factor regressions			
Decile	Return	Market	3-factor	4-factor	RM	HML	SMB	UMD
Low β^θ	1.14	0.07	0.09	0.06	1.16	-0.11	0.37	0.03
2	1.09	0.13	0.12	0.13	1.04	0.02	-0.02	-0.01
3	1.05	0.13	0.10	0.13	0.98	0.06	-0.08	-0.03
4	0.99	0.09	0.06	0.07	0.95	0.09	-0.10	-0.01
5	0.99	0.10	0.03	0.03	0.97	0.15	-0.11	0.00
6	0.97	0.07	0.04	0.02	0.97	0.09	-0.10	0.02
7	0.96	0.05	0.05	0.05	0.97	0.02	-0.08	0.00
8	0.92	-0.02	-0.02	0.02	1.00	-0.03	0.01	-0.03
9	0.82	-0.20	-0.17	-0.13	1.10	-0.12	0.17	-0.04
High β^θ	0.64	-0.48	-0.44	-0.37	1.17	-0.23	0.62	-0.07
Low-High	0.50	0.55	0.53	0.43	-0.01	0.12	-0.25	0.10
t-statistic	[3.60]	[3.95]	[3.86]	[3.06]	[-0.32]	[2.29]	[-5.32]	[2.98]

Notes: 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 are held without rebalancing for 12 month beginning in month $\tau + 2$. The sample period is 1954-2009.

Table 4. Summary Statistics of Factor Returns

	Mean	Standard Deviation	Sharpe Ratio	Correlations			
				LMT	RM	HML	SMB
LMT	0.4985	3.5864	0.1390				
RM	0.5315	4.3876	0.1211	-0.1118			
HML	0.4052	2.7914	0.1452	0.1233	-0.2899		
SMB	0.2033	2.9961	0.0679	-0.2369	0.2724	-0.2265	
UMD	0.7497	4.1139	0.1822	0.1065	-0.1314	-0.1797	-0.0317

Notes: This table reports summary statistics for the difference in returns on stocks with low and high loadings β^{θ} on the labor market tightness (LMT) as well as for market excess return (RM), and value (HML), size (SMB), and momentum (UMD) factors. All data are monthly. Means and standard deviations are in percent. The sample period is 1954-2009.

Table 5. FUTURE PERFORMANCE AND RISK LOADINGS OF PORTFOLIOS SORTED BY LOADINGS ON LABOR MARKET TIGHTNESS FACTOR: ROBUSTNESS

	Raw	Alphas			Loadings from 4-factor regressions			
	Return	Market	3-factor	4-factor	RM	HML	SMB	UMD
A. Non-overlapping portfolios								
Low-High	0.62	0.69	0.58	0.55	-0.02	0.27	-0.26	0.04
t-statistic	[3.75]	[4.12]	[3.55]	[3.23]	[-0.39]	[4.36]	[-4.56]	[0.88]
B. One-month holding								
Low-High	0.59	0.67	0.66	0.51	-0.05	0.14	-0.28	0.15
t-statistic	[3.44]	[3.89]	[3.82]	[2.91]	[-1.17]	[2.12]	[-4.80]	[3.47]
C. Two-months waiting								
Low-High	0.49	0.54	0.52	0.42	-0.01	0.11	-0.25	0.10
t-statistic	[3.56]	[3.89]	[3.82]	[3.02]	[-0.26]	[2.16]	[-5.32]	[2.96]
D. Excluding micro caps								
Low-High	0.48	0.51	0.50	0.36	-0.02	0.08	0.00	0.13
t-statistic	[3.96]	[4.17]	[3.96]	[2.84]	[-0.76]	[1.73]	[0.10]	[4.40]
E. Alternative definition of ϑ								
Low-High	0.42	0.46	0.44	0.42	-0.01	0.10	-0.19	0.02
t-statistic	[3.08]	[3.31]	[3.16]	[2.94]	[-0.38]	[1.86]	[-4.00]	[0.53]

Notes: This table reports average raw returns and alphas, in percent per month, loadings, and corresponding t-statistics from the four-factor model regressions 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 for one 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 below 20th percentile of NYSE market capitalization are excluded from the sample, and the remaining firms are assigned into deciles at the end of every month τ and are held without rebalancing for 12 month beginning in month $\tau+2$. In Panel E, labor market tightness factor is defined as 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 all panels, the sample period is 1954-2009.

Table 6. Fama-MacBeth Regressions of Annual Stock Returns on Loadings on Labor Market Tightness Factor and Other Variables

Reg	Const	β^{θ}	β^{M}	ME	BM	RU	HN	IK	AG
(1)	0.388	-0.025	-0.012	-0.019					
	[4.28]	[-2.13]	[-0.77]	[-2.79]					
(2)	0.326	-0.025	-0.001	-0.014	0.038				
	[3.63]	[-2.09]	[-0.04]	[-1.97]	[4.07]				
(3)	0.336	-0.029	0.004	-0.016	0.037	0.047			
	[3.75]	[-2.50]	[0.28]	[-2.27]	[4.19]	[2.83]			
(4)	0.372	-0.036	-0.001	-0.019	0.028	0.062	-0.059		
	[4.13]	[-2.86]	[-0.08]	[-2.81]	[2.36]	[2.94]	[-4.14]		
(5)	0.386	-0.038	0.000	-0.019	0.026	0.061		-0.024	
	[4.02]	[-2.88]	[0.02]	[-2.74]	[2.32]	[2.77]		[-1.92]	
(6)	0.363	-0.029	0.003	-0.017	0.025	0.058			-0.070
	[3.90]	[-2.37]	[0.22]	[-2.40]	[2.46]	[2.94]			[-3.43]
(7)	0.379	-0.035	0.001	-0.019	0.023	0.061	0.001		-0.085
	[4.23]	[-2.76]	[0.06]	[-2.87]	[2.06]	[2.90]	[0.04]		[-5.55]
(8)	0.414	-0.039	-0.011	-0.021	0.019	0.057	0.038	0.060	-0.170
	[4.15]	[-3.03]	[-0.53]	[-2.96]	[1.60]	[2.47]	[0.89]	[1.72]	[-2.84]

Notes: This table reports the results of annual Fama-MacBeth regressions. Stock returns from month 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 are new hiring, investment, and asset growth rates, respectively, defined as in Bazdresch, Belo, and Lin (2012). Reported are average coefficients and the corresponding t-statistics. The sample period is 1960-2009. Details of variable definitions are in the Appendix.

Table 7. Two-Pass Regressions, Industry Portfolios

Reg	RM	ϑ	HML	SMB	UMD	R^2
(1)	0.000					-0.020
	[-0.26]					
(2)	0.001	-0.021				0.107
	[1.05]	[-2.75]				
(3)	0.001		-0.002	-0.001		0.102
	[0.47]		[-2.18]	[-1.63]		
(4)	0.002	-0.017	-0.002	-0.001		0.169
	[1.38]	[-2.15]	[-2.46]	[-1.27]		
(5)	0.002		-0.001	-0.001	0.005	0.145
	[1.37]		[-1.73]	[-1.80]	[1.97]	
(6)	0.004	-0.016	-0.001	-0.001	0.003	0.211
	[2.12]	[-2.06]	[-2.00]	[-1.45]	[1.30]	

Notes: This table reports results of two-pass regressions on 48 value-weighted industry portfolios. In the first pass, excess returns of each portfolio are regressed on factors shown in column headings. Next, average excess returns of the industry portfolios are regressed on the loadings from the first-stage regressions. Shown are coefficients, corresponding *t*-statistics, and adjusted R^2 values from the second-stage regressions. Sample period is 1954-2009.

Table 8. Benchmark Parameter Calibration

Parameter	Notation	Value
Aggregate shock and preference		
Persistence of aggregate productivity shock x	ρ_x	0.9830
Conditional standard deviation of x	σ_x	0.0077
Persistence of participation shock p	ρ_p	0.9967
Conditional standard deviation of p	σ_p	0.0033
Average risk-free rate	$\bar{r}_f$	0.005
Affine coefficient of $r_{f,t}$	B	-0.20
Price of risk on shock x	γ_x	24
Price of risk on shock p	γ_p	28
Labor market parameters		
Average monthly job quit rate	s	0.023
Matching function elasticity	ξ	1.28
Returns to scale of labor	α	0.65
Bargaining power of worker	η	0.3
Flow cost of vacancy posting	κ_h	0.60
Flow cost of firing	κ_f	0.85
Benefit of being unemployed	b	0.49
Idiosyncratic shock process		
Persistence of idiosyncratic productivity shock z	ρ_z	0.96
Conditional standard deviation of z	σ_z	0.08

Notes: This table lists the parameter values in the benchmark calibration. The model is based on a monthly frequency. We calibrate the aggregate productivity shock to nonfarm business labor productivity (output per hour) index reported by BLS. We estimate ρ_x and σ_x by fitting an AR(1) process for the percentage deviation from trend of the quarterly series of labor productivity, and transforming to monthly frequency according to Heer and Mauner (2011). Similarly, we normalize the labor force participation rate and fit AR(1) process to estimate ρ_p and σ_p. We set $\overline{r_f}$, and B to match the time series mean and standard deviation of risk free rate. γ_x, γ_p are set to match the average market excess return and Sharpe ratio. We base the monthly job quit rate on JOLT, as in den Haan, Ramey, and Watson (2000) and Davis, Faberman, and Haltiwanger (2012). Matching parameter ξ is derived from the steady state value of job finding rate 0.45 and vacancy filling rate 0.71, following Shimer (2005). η, κ_h, κ_f, α, b, ρ_z and σ_z are calibrated jointly to match the model simulated moments with a set of empirical moments in Table 9.

Table 9. Aggregate and Firm-specific Target Moments

Moments	**Data**	**Model**
Unemployment rate	0.057	0.051
Labor share of income	0.717	0.731
Stdev of real wage growth relative to output growth	0.483	0.382
Stdev of dividend growth relative to output growth	3.630	3.006
Total adjustment costs to total output	0.020	0.019
Annual inaction fraction	0.070	0.063
Dispersion of annual employment growth rates	0.250	0.261
Volatility of annual employment growth rates	0.200	0.180

Notes: This table summarizes the empirical aggregate and firm-specific moments used to calibrate model parameters $(\eta, \kappa_h, \kappa_f, \alpha, b, \rho_z, \sigma_z)$. The model moments are generated using the benchmark calibration in Table 8, and by a simulation of 100 artificial panels each with 5,000 firms and 5300 months, with the initial 300 months serving as burn-in periods. The average unemployment rate is from BLS. The aggregate labor share of income equals total wage compensation of the economy over total output. Gourio (2007) reports the standard deviation of log-changes of firm-specific wage rate relative to output is 0.483, and that for aggregate after-tax profit is 3.63. Total adjustment costs of a year equal the sum of vacancy posing costs and firing costs for all firms. The average annual inaction fraction accounts the average percentage of Compustat firms with zero net annual employment growth rate during 1980 - 2010. We obtain the average dispersion of annual employment growth rates by taking the cross-sectional standard deviation of Compustat firm for each year, then take the time series average. We follow the moving average formula in Davis, Haltiwanger, Jarmin and Miranda (2006) to get the employment-weighted average volatility of annual employment growth rates.

Table 10. Forecasting Regressions

θ_{t+1}		$R^e_{M,t+1}$	
τ_0	-0.05	ν_0	0.01
τ_θ	0.81	ν_θ	-0.01
$\tau_{x,0}$	-3.07	$\nu_{x,0}$	-6.02
$\tau_{p,0}$	3.83	$\nu_{p,0}$	-11.16
$\tau_{x,1}$	3.76	$\nu_{x,1}$	6.01
$\tau_{p,1}$	-3.94	$\nu_{p,1}$	11.04
R^2	98.18%	R^2	94.71%

Notes: This table reports the estimates of the equilibrium forecasting rule for labor market tightness specified in (22), as well as the affine function of market excess return in (24). Goodness-of-fit measures R^2 are also reported.

Table 11. Portfolio in Benchmark Model vs. Data
Sorted by Loadings on Labor Market Tightness Factor

	Data			Benchmark Model		
Decile	β_θ	Ret	HN	β_θ	Ret	HN
Low	-0.85	13.68	6.76	-0.13	13.64	1.59
2	-0.41	13.08	8.28	-0.06	13.06	2.26
3	-0.24	12.60	5.93	-0.01	12.52	12.47
4	-0.12	11.88	7.16	0.01	12.27	-2.90
5	-0.02	11.88	5.56	0.04	11.71	22.67
6	0.07	11.64	5.56	0.07	11.78	-8.97
7	0.17	11.52	6.41	0.13	11.09	16.27
8	0.30	11.04	6.38	0.15	10.95	-2.10
9	0.49	9.84	8.01	0.20	10.28	8.36
High	0.99	7.68	8.05	0.27	9.29	-4.45
Low-High	1.84	6.00		0.40	4.34	

Notes: This table compares our benchmark model performance with data. All numbers are expressed in percentage terms. Return refers to future portfolio equity return. HN stands for employment growth rate. 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 loadings and calculate the realized and expected future annualized equity returns and annualized employment growth rate. The benchmark model produces monotonically decreasing portfolio returns and non-monotonic employment growth rate, which resembles the data. Note that our model does not consider economic growth, hence firms do not necessarily experience positive employment growth rate on average as in data.

Table 12. Simulated Portfolio Returns
Sorted by Loadings on ϑ Factor, different rebalancing horizon

Decile	1 month	2 months	4 months	6 months	12 months
Low	13.64	13.57	13.49	13.41	13.22
2	13.06	13.00	12.94	12.88	12.74
3	12.52	12.55	12.51	12.46	12.35
4	12.27	12.36	12.32	12.28	12.19
5	11.71	11.85	11.82	11.80	11.75
6	11.78	11.79	11.78	11.76	11.72
7	11.09	11.21	11.21	11.21	11.22
8	11.95	11.02	11.03	11.04	11.07
9	10.28	10.39	10.42	10.46	10.55
High	9.29	9.48	9.55	9.62	9.82
Low-High	4.34	4.09	3.94	3.79	3.40

Notes: This table reports the simulated return spread among portfolios sorted by the ϑ factor loadings from the benchmark model, with portfolios rebalanced after one month, two months, four months, six months, and 12 months. As we increase the rebalancing horizon, the cross-section portfolio spread decreases slightly and monotonically. This is because the longer the portfolio holding horizon, the more noise we accumulate, hence the weaker the predicative power will be for future returns. However, we still get a significant and sizable spread even at a one year rebalancing horizon, indicating the robustness of our model prediction.

Table 13. PORTFOLIO RETURN MODEL COMPARISON
SORTED BY LOADINGS ON LABOR MARKET TIGHTNESS FACTOR

Decile	Data	Benchmark	Model 1	Model 2	Model 3
Low	13.68	13.64	12.63	10.40	12.51
2	13.08	13.06	12.11	11.06	12.06
3	12.60	12.52	12.15	11.50	11.70
4	11.88	12.27	11.46	11.64	11.53
5	11.88	11.71	12.02	12.04	11.12
6	11.64	11.78	11.20	12.08	11.05
7	11.52	11.09	12.05	12.44	10.58
8	11.04	10.95	11.09	12.57	10.40
9	9.84	10.28	11.45	12.89	9.87
High	7.68	9.29	11.39	13.27	9.06
Low-High	6.00	4.34	1.25	-2.88	3.45

Notes: This table compares the model simulated expected future equity returns of 10 portfolios sorted by the loadings on labor market tightness factor with their empirical counterpart. Benchmark stands for the benchmark labor capital asset pricing model that we propose in this paper. Model 1 is an economy with the same two aggregate shocks, but no equilibrium mechanism in the labor market. Model 2 is obtained by turning off the participation shock in our benchmark model, i.e. is a one-factor labor market equilibrium model with aggregate technology shock only. Model 3 is obtained by turning off the aggregate technology shock in the benchmark model, i.e. is a one-factor labor market equilibrium model with participation shock only. Note that in Model 2 and Model 3, loadings on the labor market tightness factor are univariate loadings without controlling for market excess return.

Table A1. Future Performance of Portfolios Sorted by Loadings on Market and Labor Market Tightness Factors

	Low β^M	2	3	4	High β^M	Low-High	
A. Independent sorts							
Low β^θ	0.64	0.62	0.54	0.50	0.34	0.29	[1.58]
2	0.62	0.55	0.55	0.44	0.23	0.39	[2.30]
3	0.58	0.58	0.52	0.35	0.15	0.43	[2.54]
4	0.63	0.53	0.43	0.23	0.22	0.41	[2.39]
High β^θ	0.28	0.33	0.21	0.10	0.03	0.25	[1.32]
Low-High	0.36	0.29	0.34	0.40	0.31		
t-statistic	[2.33]	[2.35]	[2.62]	[2.92]	[2.47]		
B. Conditional sorts: first on β^θ, then on β^M							
Low β^θ	0.62	0.62	0.47	0.43	0.34	0.28	[1.45]
2	0.63	0.58	0.57	0.48	0.33	0.29	[1.89]
3	0.60	0.59	0.51	0.43	0.21	0.39	[2.59]
4	0.66	0.54	0.40	0.28	0.17	0.49	[3.04]
High β^θ	0.31	0.31	0.05	0.06	0.01	0.30	[1.50]
Low-High	0.31	0.31	0.42	0.37	0.33		
t-statistic	[2.07]	[2.47]	[3.12]	[2.74]	[2.38]		
C. Conditional sorts: first on β^M, then β^θ							
Low β^θ	0.70	0.61	0.54	0.52	0.32	0.38	[1.98]
2	0.62	0.54	0.56	0.42	0.21	0.41	[2.36]
3	0.55	0.57	0.50	0.35	0.20	0.35	[2.04]
4	0.63	0.54	0.46	0.20	0.13	0.50	[2.84]
High β^θ	0.33	0.39	0.26	0.10	-0.10	0.43	[2.05]
Low-High	0.37	0.22	0.28	0.42	0.42		
t-statistic	[2.62]	[2.02]	[2.43]	[3.15]	[2.85]		

Notes: This table reports average raw returns, in percent per month, for the quintiles portfolios of stocks sorted on the basis of their loadings on the labor market tightness and market factors, as well as for the portfolio that is long the low quintile and short the high quintile. Firms are assigned into groups at the end of every month τ and are held without rebalancing for 12 months beginning in month $\tau+2$. The bottom row and the last columns give t-statistics for the low-high portfolios. The sample period is 1954-2009.

Table A2. FAMA-MACBETH REGRESSIONS OF ANNUAL STOCK RETURNS ON LOADINGS ON COMPONENTS OF LABOR MARKET TIGHTNESS FACTOR AND OTHER VARIABLES

Reg	Const	β^M	β^{LFPR}	β^{Unemp}	β^{Vac}	β^{IP}	Controls
(1)	0.163	-0.011	0.000				No
	[5.91]	[-0.75]	[0.16]				
(2)	0.162	-0.012		0.009			No
	[5.93]	[-0.78]		[1.12]			
(3)	0.163	-0.010			-0.006		No
	[5.93]	[-0.65]			[-0.76]		
(4)	0.159	-0.008				-0.002	No
	[5.91]	[-0.54]				[-1.02]	
(5)	0.160	-0.011	0.000	0.013	0.004		No
	[5.89]	[-0.76]	[-0.04]	[1.44]	[0.56]		
(6)	0.156	-0.009	0.000	0.010	0.007	-0.002	No
	[5.88]	[-0.62]	[0.82]	[1.12]	[0.81]	[-1.00]	
(7)	0.429	-0.034	0.005				Yes
	[3.64]	[-0.97]	[1.18]				
(8)	0.401	-0.013		0.018			Yes
	[4.01]	[-0.62]		[2.32]			
(9)	0.418	-0.005			-0.023		Yes
	[4.13]	[-0.31]			[-2.82]		
(10)	0.411	-0.021				-0.004	Yes
	[3.97]	[-0.74]				[-1.32]	
(11)	0.431	-0.012	0.005	0.004	-0.022		Yes
	[3.49]	[-0.62]	[1.18]	[0.28]	[-1.30]		
(12)	0.307	-0.023	0.008	0.000	0.026	0.016	Yes
	[3.41]	[-0.85]	[1.15]	[0.01]	[0.79]	[0.98]	

Notes: This table reports the results of annual Fama-MacBeth regressions. Stock returns from month July of year t to June of year $t+1$ are regressed on β^M, market beta measured using three years of data ending in end of May of year t; β^{LFPR}, β^{Unemp}, β^{Vac}, and β^{IP}, loadings from two-factor regressions of stock excess returns on market excess returns and log changes in either labor force participation rate, unemployment rate, vacancy rate, or industrial production, respectively, computed over the same period as β^M. Controls include log of market equity measured as of the end of June of year t; log of the ratio of book equity to market equity measured following Davis, Fama, and French (2000); 12-month stock return ending in June of year t; and new hiring, investment, and asset growth rates, defined as in Bazdresch, Belo, and Lin (2012). Reported are average coefficients and the corresponding t-statistics. The sample period is 1960-2009. Details of variable definitions are in the Appendix.