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

JEL Classification: E24, G12, J21

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

Building on the seminal contributions of Diamond (1982), Mortensen (1982), and Pissarides (1985), we show that labor search frictions are an important determinant of the cross-section of equity returns. In search models, firms post vacancies to attract workers, and unemployed workers look for jobs. The likelihood of matching a worker with a vacant job is determined endogenously and depends on the congestion of the labor market, which is measured as the ratio of vacant positions to unemployed workers. This ratio, termed *labor market tightness*, is the key variable of our analysis. Intuitively, recruiting new workers becomes more costly when this ratio increases.

We begin by studying the empirical relation between labor market conditions and the cross-section of equity returns. We measure aggregate labor market tightness as the ratio of the monthly vacancy index published by the Conference Board to the unemployed population (cf. Shimer (2005)). To measure the sensitivity of firm value to labor market conditions, we estimate loadings of equity returns on log changes in labor market tightness controlling for the market return. We use rolling firm-level regressions based on three years of monthly data to allow for time variation in the loadings. Using the panel of U.S. stock returns from 1951 to 2012, we show that loadings on changes in the labor market tightness robustly and negatively predict future stock returns in the cross-section. Sorting stocks into deciles on the estimated loadings, we find an average spread in future returns of firms in the low- and high-loading portfolios of 6% per year. We emphasize that this return differential is not due to mispricing. While it cannot be attributed to differences in loadings on commonly considered risk factors, such as those of the CAPM or the Fama and French (1993) three-factor model,

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

it arises rationally in our theoretical model due to risk associated with labor market frictions as we describe in detail below.

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

Our results hold not only when controlling for firm-level characteristics as in Fama-MacBeth regressions but also after accounting for macro variables. For example, labor market tightness and industrial production are correlated and highly procyclical. However, we show that loadings on labor market tightness contain information about future returns, while loadings on industrial production do not. We also find that, unlike many cross-sectional predictors of equity returns that are priced mainly within industries, labor market tightness loadings contain information about future returns when considered both within and across industries. Additional robustness tests confirm our results; for example, excluding micro stocks has a negligible effect on the return spread across labor market tightness portfolios.

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

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

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

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

Our model replicates the negative relation between loadings on labor market tightness and expected returns. Intuitively, firm policies are driven by opposing cash flow and discount rate effects. On the one hand, positive shocks to matching efficiency lower marginal hiring costs. This cash flow channel implies an increase in optimal vacancies postings. On the other hand, positive shocks to matching efficiency are associated with an increase in discount rates. This assumption is consistent with the general equilibrium view that positive efficiency shocks lead to lower consumption as firms incur higher total hiring costs. This discount rate channel implies a reduction in the present value of job creation, and hence a decrease in optimal vacancy postings. As an equilibrium outcome of the labor market, the cash flow channel dominates the discount rate effect at the aggregate level. Thus, labor market tightness is positively related to matching efficiency shocks, so that loadings on labor market tightness are positively related to return exposures to matching efficiency shocks.

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

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

Our paper also adds to the production-based asset pricing literature pioneered by Cochrane (1991) and Jermann (1998). Starting with Berk, Green, and Naik (1999), a large literature studies cross-sectional asset pricing implications of firm-level real investment decisions (e.g., Gomes, Kogan, and Zhang (2003), Carlson, Fisher, and Giammarino (2004), Zhang (2005), and Cooper (2006)). More closely related are Papanikolaou (2011) and Kogan and Papanikolaou (2012, 2013) who highlight that investment-specific shocks are related to firm-level risk premia. We differ by studying frictions in the labor market and specifically shocks to the efficiency of the matching technology.

The impact of labor market frictions on the aggregate stock market has been analyzed by Danthine and Donaldson (2002), Merz and Yashiv (2007), Lochstoer and Bhamra (2009), and Kuehn, Petrosky-Nadeau, and Zhang (2012).[2] A related line of literature links cross-sectional asset prices to labor-related firm characteristics. Gourio (2007), Chen, Kacperczyk, and Ortiz-Molina (2011), and Favilukis and Lin (2012) consider labor operating leverage arising from rigid wages; Donangelo (2012) focuses on labor mobility; Palacios (2013) studies labor intensity as measured by the ratio of wages to revenue; Ochoa (2013) investigates the risk implications of skilled labor; and Eisfeldt and Papanikolaou (2013) study organizational capital embedded in specialized labor input. We differ by exploring the impact of search costs on cross-sectional asset prices.

Closest to our paper is Belo, Lin, and Bazdresch (2014), who also emphasize that firms' hiring policies affect cross-sectional risk premia. They find that hiring growth rates predict returns in the data and explain this finding with a neoclassical Q-theory model with labor and capital adjustment costs. In contrast, we base our analysis on conditional risk loadings rather than firm-level characteristics, and emphasize the risk implications arising in a partial-equilibrium labor search model. Recruiting workers in congested labor market is costly and firms' sensitivity to the tightness of the labor markets affects their valuation.

[2] Whereas we consider labor market frictions, human capital risk is studied by Jagannathan and Wang (1996), Berk and Walden (2013), and Eiling (2013).

I. Empirical Results

In this section, we document a robust negative relation between stock return loadings on changes in labor market tightness and future equity returns. We establish this result by studying portfolios sorted by loadings on labor market tightness and confirm it using Fama-MacBeth (1973) regressions. We also show that these loadings forecast 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. Availability of labor market data restricts our analysis to the 1951 to 2012 period. Fama-MacBeth regressions additionally require Compustat data on book equity and other firm-level attributes. Consequently, the analysis based on those data is conducted for the 1960 to 2012 sample. In Appendix A, we list the exact formulas for firm characteristics used in our tests.

B. Labor Market Tightness

We obtain the monthly labor force participation and unemployment rates from the Current Population Survey of the Bureau of Labor Statistics for the years 1951 to 2012. The traditionally used measure of vacancies has been the Conference Board's Help Wanted Index, which was based on advertisements in 51 major newspapers. In 2005, Conference Board replaced it with Help Wanted Online, recognizing the importance of online marketing. We follow Barnichon (2010), who combines the print and online data to create a composite vacancy index starting in 1995.[3]

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

[3] The data are available on his website, http://sites.google.com/site/regisbarnichon/.

strongly procyclical and persistent as in Shimer (2005). The cyclical nature of θ_t is driven by the pro-cyclicality of vacancies, its numerator, and the counter-cyclicality of the number of unemployed workers, its denominator.

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

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

Table I reports the time series properties of ϑ_t, its components, and other macro variables. We consider changes in the Industrial Production Index (IP) from the Board of Governors, changes in the Consumer Price Index (CPI) from the Bureau of Labor Statistics, the dividend yield of the S&P 500 Index (DY) as computed by Fama and French (1988), the term spread (TS) between 10-year and 3-month Treasury constant maturity yields, and the default spread (DS) between Moody's Baa and Aaa corporate bond yields.

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

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

$$R^e_{i,t} = \alpha_{i,\tau} + \beta^M_{i,\tau} R^e_{M,t} + \beta^\theta_{i,\tau} \vartheta_t + \varepsilon_{i,t}, \tag{3}$$

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

C. Portfolio Sorts

At the end of each month τ, we rank stocks into deciles by loadings on labor market tightness $\beta^{\theta}_{i,\tau}$, 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 reduces noise due to seasonalities. We show robustness to alternative portfolio formation methods in the next section.

Table II presents average firm characteristics of the resulting decile portfolios. Average loadings on labor market tightness (β^{θ}) range from -0.80 for the bottom decile to 0.91 for the top decile. Firms in the high and low groups are on average smaller with higher market betas than firms in the other deciles, as is often the case when firms are sorted on estimated loadings. No strong relation emerges between loadings on labor market tightness and any of the other considered characteristics: book-to-market ratios (BM), stock return run-ups (RU), asset growth rates (AG), investment rates (IR), and hiring rates (HN). The lack of a relation between loadings on labor market tightness and hiring rates is of particular interest, as it provides the first evidence that our empirical results are distinct from those of Belo, Lin, and Bazdresch (2014).

For each decile portfolio, we obtain monthly time series of returns from January 1954 until December 2012. Table III summarizes returns, alphas, and betas of each decile and of the portfolio that is long the decile with low loadings and short the decile with high loadings on labor market tightness. To control for differences in risk across deciles, we present unconditional alphas from the CAPM, Fama and French (1993) 3-factor model, and Carhart (1997) 4-factor model. We account for possible time variation in betas and risk premiums by calculating conditional alphas following either Ferson and Schadt (1996) (FS) or Boguth, Carlson, Fisher, and Simutin (2011) (BCFS).[4] The last four columns of the table show market (MKT), value (HML), size (SMB), and momentum (UMD) betas of each decile. Firms in the high decile have somewhat larger size betas and lower momentum loadings.

Both raw and risk-adjusted returns of the ten portfolios indicate a strong negative relation between loadings on the labor market tightness factor and future stock performance. Firms in the low β^{θ} decile earn the highest average return, 1.12% monthly, whereas the high β^{θ} decile performs most poorly, generating on average just 0.65% return per month. The difference in performance of the two deciles, at 0.47%, is economically large and statistically significant (t-statistic of 3.41). The corresponding differences in both unconditional and conditional alphas are similarly striking, ranging from 0.41% (t-statistic of 2.99) for Carhart 4-factor alphas to 0.52% (t-statistic of 3.83) for Fama-French 3-factor alphas. Conditional alphas are similar in magnitude to unconditional ones, suggesting negligible time variation in betas.

Results of portfolio sorts thus strongly suggest that loadings on labor market tightness are an important predictor of future returns. To evaluate robustness of this relation over time, we plot the cumulative returns (Panel A) and monthly returns (Panel B) of the long-short β^{θ} portfolio in Figure 2. The cumulative return steadily increases throughout the sample period, indicating that the relation between loadings on labor market tightness and future stock returns persists over time. Table IV presents summary statistics for returns on this portfolio and for market, value, size, and momentum factors. The long-short labor market tightness portfolio is as volatile as the market and momentum factors and achieves a Sharpe ratio (0.13) comparable to that of the market and the value factors.

We emphasize that although the difference in returns of firms with low and high loadings on labor market tightness cannot be explained by the commonly considered factor models, this difference should not be interpreted as mispricing. It arises rationally in our theoretical

[4] More specifically, we calculate conditional alphas as intercepts from regression

$$R^e_{j,t} = \alpha_j + \beta_j \begin{bmatrix} 1 & Z_{t-1} \end{bmatrix}' R^e_{M,t} + e_{j,\tau}, \tag{4}$$

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

framework as compensation for risk associated with labor market frictions. The commonly used factor models such as the CAPM do not capture this type of risk. Consequently, alphas from such models are different for firms with different loadings on labor market tightness.

D. Robustness of Portfolio Sorts

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

The portfolio formation design employed in the previous section is motivated by investment strategies such as momentum. It involves holding 12 overlapping portfolios and reduces noise due to seasonalities. We consider two alternatives: forming portfolios only once a year (Panel A) and holding the portfolios for one month (Panel B). Both alternatives ensure that no portfolios overlap. Panels A and B of Table V show that each of these approaches results in even more dramatic differences in future performance of low and high β^{θ} deciles. For example, the difference in average returns of the low and high deciles reaches 0.55% monthly when portfolios are formed once a year, compared to 0.47% reported in Table III.

We next explore the sensitivity of the results to the length of time between calculating β^{θ} and forming portfolios. Our base case results in Table III are obtained by assuming that all variables needed to compute labor market tightness (vacancy index, unemployment rate, and labor force participation rate) are publicly available within a month. The assumption is well-justified in current markets, where the data for any month are typically available within days after the end of that month. To allow for a slower dissemination of data in the earlier sample, we consider a two-month waiting period. Panel C of Table V shows that the results are not sensitive to this change in methodology. The difference in future returns of stocks with low and high loadings on labor market tightness reaches 0.47% per month.

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

In Panel E of Table V we evaluate robustness to excluding microcaps, which we define as stocks with market equity below the 20th NYSE percentile. Microcaps on average represent just 3% of the total market capitalization of all stocks listed on NYSE, Amex, and Nasdaq, but they account for approximately 60% of the total number of stocks. Excluding these stocks from the sample does not meaningfully impact the results.[5]

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

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

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

The disadvantage of both of these approaches is that they introduce a look-ahead bias as the entire sample is used to estimate the labor market tightness factor. Yet, the first alternative definition allows us to focus on the component of labor market tightness that is unrelated to macro variables, which may have non-zero prices of risk. The second definition allows us to focus on the unpredictable component of labor market tightness. Panels F and G of Table V show that our results are little affected by the changes in the definition of the labor market tightness factor. The difference in future raw and risk-adjusted returns of portfolios

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

with low and high loadings on the factor are always statistically significant and economically important, ranging between 0.41% and 0.51% monthly.

In Table III, we compute alphas from multi-factor models to ensure that the relation between loadings on labor market tightness and future equity returns is not driven by differences in loadings on known risk factors. For robustness, we also consider modifying regression (3) to include size, value and momentum factors. Panel H of Table V shows that our results are not sensitive to this alternative method for estimating β^{θ}.

We provide additional robustness tests in the Internet Appendix. In Tables IA.I and IA.II, we control for the liquidity and profitability factors, and summarize post-ranking β^{θ} loadings of the decile portfolios. We also evaluate the relation between loadings on labor market tightness and future equity returns conditional on stocks' market betas β^{M}. Table IA.III shows that, irrespective of whether we consider independent or dependent sorts, stocks with low loadings on labor market tightness significantly outperform stocks with high loadings.

E. Fama-MacBeth Regressions

The empirical evidence from portfolio sorts provides a strong indication of a negative relation between stock return loadings on changes in labor market tightness and subsequent equity returns. However, such univariate analysis does not account for other firm-level characteristics that have been shown to relate to future returns. We compare the loadings on the labor market tightness factor to other well-established determinants of the cross-section of stock returns. Our goal is to evaluate whether the ability of β^{θ} to forecast returns is subsumed by other firm-level characteristics. To this end, we run annual Fama-MacBeth (1973) regressions

$$R^{e}_{i,T+1} = \gamma^{0}_{T} + \gamma^{1}_{T}\beta^{\theta}_{i,\tau} + \sum_{j=1}^{K} \gamma^{j}_{T} X^{j}_{i,T} + \eta_{i,T}, \tag{6}$$

where $R^{e}_{i,T+1}$ is stock i excess return from July of year T to June of year $T+1$, $\beta^{\theta}_{i,\tau}$ 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' measurements in the regression follows the widely accepted convention of Fama and French (1992).

We include in the Fama-MacBeth regressions commonly considered control variables such as the log of a firm's market capitalization (ME), the log of the book-to-market ratio (BM), and the return run-up (RU) (Fama and French (1992) and Jegadeesh and Titman (1993)). We also consider other recently documented determinants of the cross-section of stock returns, including the investment rate (IK) of Titman, Wei, and Xie (2004), asset growth rate (AG) of Cooper, Gulen, and Schill (2008), and the labor hiring rate (HN) of Belo, Lin, and Bazdresch (2014) and Titman, Wei, and Xie (2004). We winsorize all independent variables cross-sectionally at 1% and 99%.

Table VI summarizes the results of the Fama-MacBeth regressions. The coefficient on β^{θ} is negative and statistically significant in each considered specification, even after accounting for other predictors of the cross-section of equity returns. The magnitude of the coefficient implies that for a one standard deviation increase in β^{θ} (0.49), subsequent annual returns decline by approximately 1.5%. Average loadings of firms in the bottom and top decile portfolios are 3.5 standard deviations apart, suggesting that the difference in future stock returns of the two groups exceeds 5% per year, in line with the results presented in Table III.

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

F. Industry-Level Analysis

The ability of commonly considered firm characteristics to predict stock returns is known to be stronger when these characteristics are computed relative to industry averages. In other words, many determinants of the cross-section of stock returns are priced within rather than across industries (e.g., Cohen and Polk (1998), Asness, Burt, Ross, and Stevens (2000), Simutin (2010), Novy-Marx (2011), and Eisfeldt and Papanikolaou (2013)). We now show that unlike many other cross-sectional predictors of stock returns, β^{θ} contains more information about future returns when considered *across* rather than *within* industries. Our goal in this section is to understand how much of the negative relation between β^{θ} and future stock returns is due to industry-specific versus firm-specific (non-industry) components.

We begin our analysis by modifying the portfolio assignment methodology used above to ensure that all β^{θ} decile portfolios have similar industry characteristics. To achieve this, we sort firms into deciles within each of the 48 industries as defined in Fama and French (1997) and then aggregate firms across industries to obtain ten industry-neutral portfolios. Panel A of Table VII shows that the differences in future performance of firms with low and high loadings on the labor market tightness factor are slightly muted relative to those in Table III. For example, the return of the long-short β^{θ} portfolio reaches 0.37% monthly when portfolio assignment is done within industries, whereas the corresponding figure is 0.47% when industry composition is allowed to vary across deciles.

The larger difference in future performance of low and high β^{θ} stocks when we allow for industry heterogeneity across decile portfolios is particularly interesting given that many known premiums are largely intra-industry phenomena. This result suggests that the labor market tightness factor may be priced in the cross-section of industry portfolios. To investigate this conjecture, we assign 48 value-weighted industry portfolios into deciles on the basis of their loadings on the labor market tightness factor and study future returns of the resulting decile portfolios.[6] Panel B of Table VII shows that industries with low loadings outperform industries with high loadings by 0.34% return per month.

II. Model

The goal of this section is to provide an economic model that explains the empirical link between labor market frictions and the cross-section of equity returns. To this end, we solve

[6]Industry portfolios are from Ken French's data library. Table IA.VI of the Internet Appendix provides summary statistics for the industry portfolios.

a partial equilibrium labor market model and study its implications for stock returns. For tractability we do not model endogenous labor supply decisions from households; instead we assume an exogenous pricing kernel.

A. Revenue

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

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

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

$$\begin{aligned} x_t &= \rho_x x_{t-1} + \sigma_x \varepsilon_t^x, && (8) \\ z_{i,t} &= \rho_z z_{i,t-1} + \sigma_z \varepsilon_{i,t}^z, && (9) \end{aligned}$$

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 shocks.

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

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

The matching efficiency shock p_t follows an AR(1) process with autocorrelation ρ_p and i.i.d.

normal innovations ε_t^p:

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

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

Several recent studies empirically analyze sources of changes in matching efficiency. Using micro-data Barnichon and Figura (2013) show that fluctuations in matching efficiency can be related to the composition of the unemployment pool, such as a rise in the share of long-term unemployed or fluctuations in participation due to demographic factors, and to dispersion in labor market conditions; Herz and van Rens (2011) and Sahin, Song, Topa, and Violante (2012) highlight the role of skill and occupational mismatch between jobs and workers; Sterk (2010) focuses on geographical mismatch exacerbated by house price movements; and Fujita (2011) analyzes the role of reduced worker search intensity due to extended unemployment benefits.

B. Matching

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

$$\bar{V}_t = \int V_{i,t} d\mu_t \qquad \bar{N}_t = \int N_{i,t} d\mu_t, \tag{12}$$

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

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

$$\bar{U}_t = L - (1-s)\bar{N}_t. \tag{13}$$

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

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

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

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

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

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

C. Wages

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

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

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

Firms benefit from hiring the marginal worker not only through an increase in output by the marginal product of labor but also through a decrease in wage payment to its current workers, $Y_{i,t}/N_{i,t}$. The term $\alpha/(1-\eta(1-\alpha))$ represents a reduction in wages coming from decreasing returns to scale. At the same time, workers can extract higher wages from firms when the labor market is tighter. Unemployment benefits provide a floor to wages.[7]

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), we specify an exogenous pricing kernel and assume that both the aggregate productivity shock x_t and efficiency shock p_t are priced. The log of the pricing kernel is given by

$$\ln M_{t+1} = \ln\beta - \gamma_x(\sigma_x\varepsilon^x_{t+1} + \phi x_t) - \gamma_{p,t}(\sigma_p\varepsilon^p_{t+1} + \phi p_t), \tag{17}$$

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

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

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

The firm's Bellman equation solves

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

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

subject to equations (7)–(18). Notice that the firms' problem is well-defined given labor market tightness θ_t and expectations about its dynamics. Given optimal cum-dividend firm value $S_{i,t}$, expected excess returns are given by

$$\mathbb{E}_t[R^e_{i,t+1}] = \frac{\mathbb{E}_t[S_{i,t+1}]}{S_{i,t} - D_{i,t}} - \frac{1}{\mathbb{E}_t[M_{t+1}]}. \tag{20}$$

E. Equilibrium

In search and matching models, optimal firm employment policies depend on the dynamics of the aggregate labor market. This is typically not the case for models with labor adjustment costs based on the Q-theory. Rather, in our setup firms have to know how congested labor markets are when they decide about optimal hiring policies as next period's workforce, Equation (10), depends on aggregate labor market tightness θ via the vacancy filling rate q. At the same time, labor market tightness depends on the distribution of vacancy postings implied by the firm-level distribution μ_t and the aggregate shocks.

Equilibrium in the labor market requires that the beliefs about labor market tightness are consistent with the realized equilibrium. Consequently, the firm-level distribution enters the state space, which is given by $\Omega_{i,t} = (N_{i,t}, z_{i,t}, x_t, p_t, \mu_t)$, and labor market tightness θ_t at each date is determined as a fixed point satisfying

$$\theta_t = \frac{\int V(\Omega_{i,t}) d\mu_t}{\bar{U}_t}. \tag{21}$$

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

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

$$\mu_{t+1} = \Gamma(\mu_t, x_{t+1}, x_t, p_{t+1}, p_t). \tag{22}$$

The recursive competitive equilibrium is characterized by: (i) labor market tightness θ_t, (ii) optimal firm policies $V(\Omega_{i,t})$, $F(\Omega_{i,t})$, and firm value function $S(\Omega_{i,t})$, (iii) a law of motion Γ of the firm-level distribution μ_t, such that: (a) Optimality: Given the pricing kernel (17), Nash bargaining wage rate (16), and labor market tightness θ_t, $V(\Omega_{i,t})$ and $F(\Omega_{i,t})$ solve the firm's Bellman equation (19) where $S(\Omega_{i,t})$ is its solution; (b) Consistency: θ_t is consistent with the labor market equilibrium (21), and the law of motion Γ of the firm-level distribution μ_t is consistent with the optimal firm policies $V(\Omega_{i,t})$ and $F(\Omega_{i,t})$.

F. Approximate Aggregation

The firm's hiring and firing decisions trade off current costs and future benefits, which depend on the aggregation and evolution of the firm-level distribution μ_t. Rather than solving for the high dimensional firm-level distribution exactly, we follow Krusell and Smith (1998) and approximate it with one moment. In search models, labor market tightness θ_t is a sufficient statistic to solve the firm's problem (19) and thus enters the state vector replacing μ_t, i.e., the approximate state space is $\tilde{\Omega}_{i,t} = (N_{i,t}, z_{i,t}, x_t, p_t, \theta_t)$.

To approximate the law of motion Γ, Equation (22), we assume a log-linear functional form

$$\log \theta_{t+1} = \tau_0 + \tau_\theta \log \theta_t + \tau_x \sigma_x \varepsilon^x_{t+1} + \tau_p \sigma_p \varepsilon^p_{t+1}. \tag{23}$$

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

$$\vartheta_{t+1} = \tau_0 + (\tau_\theta - 1) \log \theta_t + \tau_x \sigma_x \varepsilon^x_{t+1} + \tau_p \sigma_p \varepsilon^p_{t+1}. \tag{24}$$

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

Our application of Krusell and Smith (1998) differs from Zhang (2005) along two dimensions. First, future labor market tightness θ_{t+1} is a function of the firm distribution at time $t+1$; hence, it is not in the information set of date t. The forecasting rule (23) at time t does not enable firms to learn θ_{t+1} perfectly, but rather to form a rational expectation about θ_{t+1}. In contrast, Zhang (2005) assumes that firms can perfectly forecast next period's industry price given time t information. If firms could perfectly forecast next period's labor market tightness, it would not carry a risk premium. Second, at each period of the simulation, we impose labor market equilibrium by solving θ_t as the fixed point in Equation (21). Hence, there is no discrepancy between the forecasted and the realized θ_{t+1}.

G. Equilibrium Risk Premia

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

$$\mathbb{E}_t[R^e_{i,t+1}] \approx \beta^x_{i,t}\lambda^x + \beta^p_{i,t}\lambda^p_t, \tag{25}$$

where $\beta^x_{i,t}$ and $\beta^p_{i,t}$ are loadings on aggregate productivity and matching efficiency shocks and λ^x and λ^p_t are their respective factor risk premia. All proofs of this section are contained in Appendix B.

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

$$R^e_{M,t+1} = \nu_0 + \nu_x\sigma_x\varepsilon^x_{t+1} + \nu_p\sigma_p\varepsilon^p_{t+1}. \tag{26}$$

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

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

$$m_{t+1} = -\gamma_{M,t}R^e_{M,t+1} - \gamma_{\theta,t}\vartheta_{t+1}, \tag{27}$$

where the prices of market risk $\gamma_{M,t}$ and labor market tightness $\gamma_{\theta,t}$ are given by

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

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

$$\mathbb{E}_t[R^e_{i,t+1}] = \beta^M_{i,t}\lambda^M_t + \beta^\theta_{i,t}\lambda^\theta_t, \tag{29}$$

where $\beta^M_{i,t}$ *and* $\beta^\theta_{i,t}$ *are the loadings on the market excess return and log-changes in labor market tightness*

$$\beta^M_{i,t} = \frac{\tau_p}{\tau_p\nu_x - \tau_x\nu_p}\beta^x_{i,t} + \frac{-\tau_x}{\tau_p\nu_x - \tau_x\nu_p}\beta^p_{i,t} \tag{30}$$

$$\beta^\theta_{i,t} = \frac{-\nu_p}{\tau_p\nu_x - \tau_x\nu_p}\beta^x_{i,t} + \frac{\nu_x}{\tau_p\nu_x - \tau_x\nu_p}\beta^p_{i,t} \tag{31}$$

and λ^M_t *and* λ^θ_t *are the respective factor risk premia given by*

$$\lambda^M_t = \nu_x\lambda^x + \nu_p\lambda^p_t \qquad \lambda^\theta_t = \tau_x\lambda^x + \tau_p\lambda^p_t. \tag{32}$$

We call relation (29) the *Labor Capital Asset Pricing Model.*[8] The goal of the model is to endogenously generate a negative factor risk premium of labor market tightness, λ^θ_t. We will explain the intuition behind Proposition 1 after the calibration in Section III.C.

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

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

$$\mathbb{E}_t[R^e_{i,t+1}] = \alpha^{CAPM}_{i,t} + \beta^{CAPM}_{i,t}\lambda^{CAPM}_t, \tag{33}$$

where the CAPM mispricing alphas are given by

$$\alpha^{CAPM}_{i,t} = \beta^\theta_{i,t}\gamma_{\theta,t}\frac{(\tau_x\nu_p - \nu_x\tau_p)^2\sigma_p^2\sigma_x^2}{\nu_x^2\sigma_x^2 + \nu_p^2\sigma_p^2}, \tag{34}$$

CAPM loadings on the market return by

$$\beta^{CAPM}_{i,t} = \frac{\nu_x\sigma_x^2}{\nu_x^2\sigma_x^2 + \nu_p^2\sigma_p^2}\beta_x + \frac{\nu_p\sigma_p^2}{\nu_x^2\sigma_x^2 + \nu_p^2\sigma_p^2}\beta_p, \tag{35}$$

and the CAPM factor risk premium $\lambda^{CAPM}_t = \lambda^M_t = \nu_x\lambda^x + \nu_p\lambda^p_t$.

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

Intuitively, this proposition states that CAPM betas are independent of the price of risk of labor market tightness $\gamma_{\theta,t}$, whereas the CAPM mispricing alphas are inversely related to labor market tightness loadings when $\gamma_{\theta,t}$ is negative. These insights are qualitatively in line with the empirical findings above and are confirmed quantitatively next.

III. Quantitative Results

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

A. Calibration

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

The labor literature provides several empirical studies to calibrate labor market parameters. Following Elsby and Michaels (2013) and Fujita and Nakajima (2013), we scale the size of labor force L to match the average unemployment rate. The elasticity of the matching function determines the responsiveness of the vacancy filling rate to changes in labor market tightness. Based on the structural estimate in den Haan, Ramey, and Watson (2000), we set the elasticity ξ at 1.27.

The bargaining power of workers η determines the rigidity of wages over the business cycle. As emphasized by Hagedorn and Manovskii (2008) and Gertler and Trigari (2009), aggregate wages are half as volatile as labor productivity. We follow their calibration strategy and set $\eta = 0.125$ to match the relative volatility of wages to output.[9] It is important to highlight that our model is not driven by sticky wages as proposed by Hall (2005) and Gertler and

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

Trigari (2009). In our model, wages are less volatile than productivity but, conditional on productivity, they are not sticky. This is consistent with Pissarides (2009), who argues that Nash bargaining wage rates are in line with wages for new hires.

If workers decide not to work, they receive the flow value of unemployment activities b. Shimer (2005) argues that the outside option for rejecting a job offer are unemployment benefits and thus sets $b = 0.4$. Hagedorn and Manovskii (2008), on the other hand, claim that unemployment activities capture not only unemployment benefits but also utility from home production and leisure. They calibrate b close to one. As in the calibration of Pissarides (2009), we follow Hall and Milgrom (2008) and set the value of unemployment activities at 0.71.[10]

The labor share of income, which Gomme and Rupert (2007) estimate to be around 0.72, is highly affected by the value of unemployment activities b and the output elasticity of labor α. Since the value of unemployment activities is close to the labor share of income, we can easily match the labor share by setting α to 0.735. We assume less curvature in the production function than, for instance, Cooper, Haltiwanger, and Willis (2007). They, however, do not model wages as the outcome of Nash bargaining.

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

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

The proportional costs of hiring and firing workers, κ_h and κ_f, determine both the overall

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

costs of adjusting the workforce as well as the behavior of firm policies. Since the literature provides little guidance on estimates of hiring costs, we set κ_h to 0.75 to match the aggregate hiring rate of workers, defined as the ratio of aggregate filled vacancies to employed labor force, $q_t\bar{V}_t/\bar{N}_t$. As hiring costs increase, firms post fewer vacancies so that the hiring rate rises. Our parameter choice is close to Hall and Milgrom (2008), who account for both the capital costs of vacancy creation and the opportunity cost of labor effort devoted to hiring activities.

Employment protection legislations are a set of rules and restrictions governing the dismissals of employees. Such provisions impose a firing cost on firms along two dimensions: a transfer from the firm to the worker to be laid off (e.g., severance payments), and a tax to be paid outside the job-worker pair (e.g., legal expenses). As the labor search literature does not provide guidance on the magnitude of this parameter, we set the flow costs of firing workers κ_f to 0.35 to match the aggregate layoff rate, defined as the ratio of total laid off workers to employed labor force, $\bar{F}_t/\bar{N}_t$. As firing costs increase, firms lay off fewer workers so that the firing rate drops.

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

We calibrate the two aggregate shocks following the macroeconomics literature. Since labor is the only input to production, aggregate productivity is typically measured as aggregate output relative to the labor hours used in the production of that output. As such, labor productivity is more volatile than total factor productivity. Similar to Gertler and Trigari (2009), we set $\rho_x = 0.95^{1/3}$ and $\sigma_x = 0.005$. Shocks to the matching efficiency tend to be less persistent but more volatile than labor productivity shocks. For instance, Andolfatto (1996) estimates matching shocks to have persistence of 0.85 with innovation volatility of 0.07 at quarterly frequency. We follow more recent estimates by Cheremukhin and Restrepo-Echavarria (2014) and set $\rho_p = 0.88^{1/3}$ and $\sigma_p = 0.025$.[11]

[11]Similar structural estimates are contained in Furlanetto and Groshenny (2012) and Beauchemin and Tasci (2012).

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

The pricing kernel is calibrated to match financial moments. We choose the time discount rate β and the pricing kernel parameters γ_x, $\gamma_{p,0}$, $\gamma_{p,1}$, and ϕ so that the model approximately matches the first and second moments of the risk-free rate and market return. This requires that β equals 0.994, $\gamma_x = 1$, $\gamma_{p,0} = -4.7$, $\gamma_{p,1} = 3.6$, and $\phi = -0.0214$. Importantly, shocks to matching efficiency carry a negative price of risk and are pro-cyclical. A small parameter value of ϕ allows for a time-varying but smooth interest rate.

Berk, Green, and Naik (1999) provide a motivation for $\gamma_x > 0$ in an economy with only aggregate productivity shocks. The assumption of $\gamma_p < 0$ can be motivated as follows. In a general equilibrium economy with a representative household, a positive matching efficiency shock increases the probability that vacant jobs are filled and thereby lowers the expected unit hiring cost. As a result, job creation becomes more attractive and firms spend more resources on hiring workers, thus depressing aggregate consumption.[12]

B. Aggregate and Firm-Level Moments

Table IX summarizes aggregate and firm-level moments computed on simulated data of the model and compares them with the data. The model closely matches firm-level and aggregate employment quantities as well as financial market moments. In equilibrium, the unemployment rate is 5.8%, the aggregate hiring rate is 3.6%, and the layoff rate is 1.4% on average, close to what we observe in the JOLTS dataset for the years 2001 to 2012.

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

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

the monthly job creation and job destruction rates are 2.6% and 2.5%, respectively, which our model replicates closely.

The model also performs well in replicating the dynamics of aggregate labor market tightness. Shimer (2005) estimates average labor market tightness of 0.63, while the model implied one is 0.65. The cyclical behavior of model-generated time series for labor market tightness, aggregate vacancies and unemployment rate match well the correlations in monthly data (for the data see Table I). Changes in labor market tightness correlate positively with changes in vacancies (0.78), and negatively with changes in the unemployment rate (-0.83). The negative relationship between changes in vacancies and unemployment rate (-0.36) is consistent with the well-known shape of the Beveridge curve.

Given our calibration strategy, the model matches well the high labor share of income (0.72), the low relative volatility of wages to output (0.55), and the small profit margin (0.11). The data for the labor share is from Gomme and Rupert (2007) and the volatility of aggregate wages to aggregate output is from Gertler and Trigari (2009). We compute the average share of corporate profits to national income using the National Income and Product Accounts as in Gourio (2007).

At the firm-level, we compute moments of annual employment growth rates as in Davis, Haltiwanger, Jarmin, and Miranda (2006) for the merged CRSP-Compustat sample for the period 1980 to 2012. The model generates the observed high volatility in annual employment growth, 23.9% in the model relative to 23.6% in the data. The proportional cost structure implies the existence of firms that are neither posting vacancies nor laying off workers. As emphasized by Cooper, Haltiwanger, and Willis (2007), we measure inaction as the fraction of firms with no change in employment, which is 9.7% for the merged CRPS-Compustat sample. In the model, this fraction is 9.9%, lending support for our modeling assumption of proportional costs.

To gauge the aggregate pricing implications, we obtain the monthly series of the value-weighted market return and one-month T-Bill rate from CRSP, and inflation from the Bureau of Labor Statistics to compute the annualized first and second moments of the one-month real risk-free rate and real market return for the period 1926 to 2012. The pricing kernel and its calibration give rise to a realistic annual average market return (8.2%) and volatility (17.2%). In addition, the average risk-free rate is low (1%) and smooth (2.1%) as in the data.

C. Equilibrium Forecasting Rules

The goal of the model is to endogenously generate a negative relation between loadings on labor market tightness and expected returns, implying a negative factor risk premium for labor market tightness, λ_t^θ. Given that aggregate productivity shocks carry a positive and efficiency shocks a negative price of risk, $\gamma_x > 0$ and $\gamma_{p,0} < 0$, Proposition 1 (Equation (32)) states that for the model to generate a negative factor risk premium for labor market tightness, it is necessary that labor market tightness reacts positively to efficiency shocks, i.e., $\tau_p > 0$.

The dynamics of labor market tightness (23) are the equilibrium outcome of firm policies and the solution to the labor market equilibrium condition (21). In particular, the endogenous response of labor market tightness to efficiency shocks, τ_p, depends on two economic forces, namely, a cash flow and a discount rate effect, which work in opposite directions. To illustrate this trade-off, we compute the Euler equation for job creation, which is given by[13]

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

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

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

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

The cash flow effect would be the only equilibrium effect in a setting in which agents are risk-neutral. Since we are interested in the pricing of labor market risks, we assume that efficiency shocks carry a negative price of risk. As a result, a positive efficiency shock leads to an increase in discount rates. This discount rate effect implies that firms reduce vacancy postings, as an increase in discount rates reduces the value of job creation, i.e., the right-hand side of the Euler equation (36). In Figure 3, the discount rate effect shifts the equilibrium labor market tightness schedule downward. If the discount rate channel dominates the cash flow channel (blue dotted line), then the new equilibrium is point D, which is associated with a drop in labor market tightness to θ_3 and thus $\tau_p < 0$.

Our benchmark calibration implies that the cash flow effect dominates the discount rate effect (dashed red line) so that labor market tightness is positively related with matching efficiency (point C in Figure 3). Quantitatively, the equilibrium labor market tightness dynamics are[14]

$$\log \theta_{t+1} = -0.0076 + 0.9827 \log \theta_t + 0.0392 \varepsilon^x_{t+1} + 0.0079 \varepsilon^p_{t+1}. \tag{37}$$

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

$$R^e_{M,t+1} = 0.0060 + 0.0096 \varepsilon^x_{t+1} - 0.0470 \varepsilon^p_{t+1}. \tag{38}$$

The average market excess return is 60 basis points per month and market prices increase with aggregate productivity shocks, $\nu_x > 0$, and decrease with efficiency shocks, $\nu_p < 0$, which is consistent with a positive price of risk for productivity shocks and a negative one for efficiency shocks.

These two dynamics allow us to compute stock return loadings on labor market tightness, which we use in the following section to form portfolios. Proposition 1 (Equation (31)) states the functional form for labor market tightness loadings, $\beta^\theta_{i,t}$. As the above discussion highlights, efficiency shocks and not productivity shocks are the driver of the labor market

[14]Note that the coefficients on the x and p shocks are normalized by their respective standard deviations as compared to Equation (23). The same normalization applies to Equation (38).

tightness premium. To illustrate the intuition behind Equation (31), we assume here that loadings on the market are constant. Labor market tightness loadings are negatively correlated with expected returns when $\nu_x/(\tau_p\nu_x - \tau_x\nu_p) > 0$. Because productivity has a positive effect on job creation, $\tau_x > 0$, and on market returns, $\nu_x > 0$, this condition reduces to $\tau_p > \nu_p$, which again emphasizes that the cash flow effect of efficiency shocks has to dominate the discount rate effect.

D. Cross-Section of Returns

In the previous section, we have shown that labor market tightness obtains a negative factor risk premium in equilibrium. To assess the extent to which the model can quantitatively explain the empirically observed negative relation between loadings on labor market tightness and future stock returns, we follow the empirical procedure of Section I on simulated data. To this end, we sort simulated firms into decile portfolios by their labor market tightness loadings, $\beta^{\theta}_{i,t}$, as defined in Proposition 1. Table X compares the simulated returns with data on industry-neutral portfolios from Panel A of Table VII.[15] As in the data, we form monthly value-weighted portfolios with annual rebalancing. The table reports average labor market tightness loadings, returns, and CAPM alphas across portfolios.

The model generates a realistic dispersion in labor market tightness loadings and returns across portfolios. The average monthly return difference between the low- and high-loading portfolios is 0.38% relative to 0.37% in the data. Moreover, the CAPM cannot explain the return differences across portfolios because in the model it does not span all systematic risks. In particular, Proposition 2 states that the CAPM alphas are inversely related to loadings on labor market tightness, as long as the market price of labor market tightness is negative.

The cash flow channel of hiring costs impacts the cross-section of returns in the following way. Due to proportional hiring and firing costs, the optimal firm policy exhibits regions of inactivity, where firms neither hire nor fire workers. Figure 4 illustrates the optimal firm policy. The horizontal black line is the optimal policy when adjusting the workforce is costless.

[15]We base our analysis on industry-neutral portfolios because the model does not capture heterogeneities across industries.

In the frictionless case, firms always adjust to the target employment size independent of the current size. The red curve is the optimal policy in the benchmark model. It displays two kinks. In the middle region, where the optimal policy coincides the dashed line, firms are inactive. In the inactivity region below the frictionless employment target, firms have too few workers but hiring is too costly (*Hiring constrained*). In the inactivity region above the frictionless employment target, firms have too many workers but firing is too costly (*Excess labor*).

Due to the time variation in matching efficiency, ideally firms would like to hire when marginal hiring costs, $\kappa_h/q(\theta, p)$, are low. This holds for the majority of firms, as aggregate vacancy postings increase with efficiency shocks. However, some firms are hit by low idiosyncratic productivity shocks such that hiring is not optimal when matching efficiency is high. For these firms, the discount rate channel dominates the cash flow channel, thereby depressing valuations. Their dividends are reduced not only by low idiosyncratic productivity shocks but also by higher wages, arising from tighter labor markets, and by firing costs. Consequently, these firms have countercyclical dividends and valuations with respect to matching efficiency shocks, which renders them more risky. Since labor market tightness loadings and loadings on matching efficiency are positively related, our model can replicate the negative relation between labor market tightness loadings and expected returns.

To illustrate that the differences in average return across portfolios are driven by the cash flow effect of matching efficiency shocks, we compute the correlation between profitability and the labor market tightness factor for each portfolio. The results are reported in the column denoted by Corr both for the data and model of Table X.[16] Consistent with the model, firms with low β^θ loadings are risky because their cash flows are counter-cyclical with respect to labor market tightness.

[16]Portfolio assignment is done within 48 industries as in Panel A of Table VII to obtain industry-neutral decile portfolios.

E. Robustness

To gain more insights about the driving forces of the model, we consider alternative calibrations in Table XI. Specifically, we are interested in the sensitivity of the return differences across β^θ-sorted portfolios to parameter values.

In specifications (1) to (3), we consider the effects of changing prices of risks, holding the first and second moments of the risk-free rate constant. Specification (1) illustrates the impact of pricing aggregate productivity shocks by setting its price to zero, $\gamma_x = 0$. The portfolio spread is of the correct sign but of smaller magnitude compared to the data. This finding indicates the importance of modeling productivity shocks to generate cross-sectional heterogeneity among firms.

In specification (2), we assume that matching efficiency shocks are not priced, $\gamma_{p,0} = 0$. We also raise the price of risk of productivity shocks to $\gamma_x = 20$, so that the Sharpe ratio of the pricing kernel matches the benchmark calibration. With only productivity shocks being priced, the cross-sectional spread is small and negative -0.18. This experiment shows that the priced variation in aggregate matching efficiency is crucial for the labor market tightness factor to affect valuations. In the benchmark calibration, we assume that the price of matching efficiency risk increases with adverse shocks. In specification (3), we assume that matching efficiency shocks have a constant price of risk, $\gamma_{p,1} = 0$. As a result, the simulated cross-sectional spread reduces from 0.38% to 0.18%, indicating the importance of the time variation in the price of risk of matching efficiency shocks.

Specifications (4) to (7) analyze the importance of labor search frictions by varying labor market parameters. For these exercises, we hold the dynamics of labor market tightness, Equation (37), constant, and study local perturbations of the parameter space. In specification (4), we increase the bargaining power of workers η by 10% to 0.1375. As a result, wages become more cyclical, implying a weaker operating leverage effect. The results suggest that this wage operating leverage channel is weak as the return spread does not change relative to the benchmark.

The next two specifications show that the costs of hiring rather than firing drive the cross-sectional return spread. In particular, reducing the costs of laying off workers κ_f by 10% to 0.315 has little effect on the return spread (specification (5)). In contrast, reducing the costs of hiring works κ_h by 10% to 0.675, decreases the return spread to 0.34% (specification (6)), compared to 0.38% for the benchmark calibration.

In the baseline calibration, we set the fixed operating costs f to match the corporate profit margin in the data. In specification (7), we reduce the fixed operating costs by 10% to 0.2034. Since the ratio of hiring costs to output is very small, $\kappa_h V/N^\alpha = 0.036$, reducing operating costs makes time-varying hiring costs less relevant for firm cash flow dynamics. As a result, the return spread drops to 0.32%.

Optimal firm employment policies depend on the equilibrium dynamics of labor market tightness (37). The log-linear structure shows that, controlling for aggregate productivity, labor market tightness proxies for unobserved matching efficiency shocks. As shown in Table X, firms' cash flow exposures to variations in labor market tightness are the source for the pricing of labor market tightness in the cross-section of returns. Consequently, the labor market tightness factor should also be a valid aggregate state variable, predicting future aggregate economic conditions.

Table XII confirms the predictability of future economic activity by labor market tightness both in the data and model. In the data, we obtain quarterly time series for the Gross Domestic Product, Wages and Salary Accruals, and Personal Dividend Income from the National Income and Product Accounts and total factor productivity from Fernald (2012). In the table, we report coefficients on labor market tightness growth, their t-statistics, and adjusted R^2 values from bivariate regressions of output growth (Panel A), wage growth (Panel B), and dividend growth (Panel C) on labor market tightness growth and total factor productivity. We run quarterly forecasting regressions for horizons up to a year.

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

IV. Conclusion

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

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

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

The model successfully replicates the observed return differential and other empirical firm-level and aggregate labor market moments. Our results suggest that labor search frictions have important implications for equity returns. Further research into the nature of interactions between labor and financial markets should provide an even more complete picture on the determinants of asset prices.

Appendix

A. Data

We use the following definitions of CRSP-Compustat variables: ME is the natural logarithm of market equity of the firm, calculated as the product of its share price and number of shares outstanding. BM is the natural logarithm of the ratio of book equity to market equity. Book equity is defined following Davis, Fama, and French (2000) as stockholders' book equity (SEQ) plus balance sheet deferred taxes (TXDB) plus investment tax credit (ITCB) less the redemption value of preferred stock (PSTKRV). If the redemption value of preferred stock is not available, we use its liquidation value (PSTKL). If 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). RU is the 12-month stock return run-up. HN is the hiring rate, calculated following Belo, Lin, and Bazdresch (2014) as $(N_t - N_{t-1})/((N_t + N_{t-1})/2)$, where N_t is then number of employees (EMP). AG is the asset growth rate, calculated following Cooper, Gulen, and Schill (2008) as $A_t/A_{t-1} - 1$, where A_t is the value of total assets (AT). IK is the investment rate, calculated following Belo, Lin, and Bazdresch (2014) as the ratio of capital expenditure (CAPX) divided by the lagged capital stock (PPENT). Profitability is defined following Cooper, Gulen, and Schill (2008) as [operating income before depreciation (OIBDP) - interest expenses (XINT) - taxes (TXT) - preferred dividends (DVP) - common dividends (DVC)] / total assets (AT).

B. Proofs

Proof of Proposition 1: A log-linear approximation of the pricing kernel M_{t+1} is given by

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

Given this approximation, the Euler equation, $\mathbb{E}_t[M_{t+1} R^e_{i,t+1}] = 0$, implies

$$\mathbb{E}_t[R^e_{i,t+1}] \approx -\mathrm{Cov}_t(m_{t+1}, R^e_{i,t+1}). \tag{39}$$

For the pricing kernel (17), the previous equation specializes to

$$\mathbb{E}_t[R^e_{i,t+1}] = \gamma_x \mathrm{Cov}_t(\sigma_x \varepsilon^x_{t+1}, R^e_{i,t+1}) + \gamma_{p,t} \mathrm{Cov}_t(\sigma_p \varepsilon^p_{t+1}, R^e_{i,t+1}). \tag{40}$$

Because $\sigma_x \varepsilon^x_{t+1} = x_{t+1} - \rho_x x_t$ and $\sigma_p \varepsilon^p_{t+1} = p_{t+1} - \rho_p p_t$, a two-factor model in x and p holds:

$$\mathbb{E}_t[R^e_{i,t+1}] = \beta^x_{i,t} \lambda^x + \beta^p_{i,t} \lambda^p_t, \tag{41}$$

where risk loadings are given by

$$\beta^x_{i,t} = \frac{\mathrm{Cov}_t(x_{t+1}, R^e_{i,t+1})}{\sigma^2_x} \qquad \beta^p_{i,t} = \frac{\mathrm{Cov}_t(p_{t+1}, R^e_{i,t+1})}{\sigma^2_p}, \tag{42}$$

and factor risk premia are

$$\lambda^x = \gamma_x \sigma^2_x \qquad \lambda^p_t = \gamma_{p,t} \sigma^2_p. \tag{43}$$

Given the pricing kernel (27) and laws of motion (24) and (26), it follows from (39) that

$$\mathbb{E}_t[R^e_{i,t+1}] = (\gamma_{M,t}\nu_x + \gamma_{\theta,t}\tau_x) \mathrm{Cov}_t(\sigma_x \varepsilon^x_{t+1}, R^e_{i,t+1}) + (\gamma_{M,t}\nu_p + \gamma_{\theta,t}\tau_p) \mathrm{Cov}_t(\sigma_p \varepsilon^p_{t+1}, R^e_{i,t+1}). \tag{44}$$

Thus, by matching coefficients in terms of covariances between equations (40) and (44), it follows that

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

implying (28) holds.

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

$$R^e_{i,t+1} - \mathbb{E}_t[R^e_{i,t+1}] = \beta^x_{i,t} \sigma_x \varepsilon^x_{t+1} + \beta^p_{i,t} \sigma_p \varepsilon^p_{t+1} + \epsilon_{i,t+1}, \tag{45}$$

with loadings defined in equation (42). Similarly, the loadings on the market return and labor market tightness satisfy the regression

$$R^e_{i,t+1} - \mathbb{E}_t[R^e_{i,t+1}] = \beta^M_{i,t} \left(R^e_{M,t+1} - \mathbb{E}_t[R^e_{M,t+1}] \right) + \beta^\theta_{i,t} (\vartheta_{t+1} - \mathbb{E}_t[\vartheta_{t+1}]) + \epsilon_{i,t+1}. \tag{46}$$

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

$$\beta^M_{i,t} \neq \frac{\mathrm{Cov}_t(R^e_{i,t+1}, R^e_{M,t+1})}{\mathrm{Var}_t(R^e_{M,t+1})} \qquad \beta^\theta_{i,t} \neq \frac{\mathrm{Cov}_t(R^e_{i,t+1}, \vartheta_{t+1})}{\mathrm{Var}_t(\vartheta_{t+1})}.$$

To compute the loadings on the market return and labor market tightness, equate Equations (45) and (46) and substitute in laws of motion (24) and (26), obtaining

$$\beta^x_{i,t}\sigma_x\varepsilon^x_{t+1}+\beta^p_{i,t}\sigma_p\varepsilon^p_{t+1}+\epsilon_{i,t+1}=\beta^M_{i,t}\left(\nu_x\sigma_x\varepsilon^x_{t+1}+\nu_p\sigma_p\varepsilon^p_{t+1}\right)+\beta^\theta_{i,t}(\tau_x\sigma_x\varepsilon^x_{t+1}+\tau_p\sigma_p\varepsilon^p_{t+1})+\epsilon_{i,t+1}.$$

By matching the coefficients in terms of $\sigma_x\varepsilon^x_{t+1}$ and $\sigma_p\varepsilon^p_{t+1}$, we get

$$\beta^x_{i,t}=\beta^M_{i,t}\nu_x+\beta^\theta_{i,t}\tau_x \qquad \beta^p_{i,t}=\beta^M_{i,t}\nu_p+\beta^\theta_{i,t}\tau_p,$$

implying that (30) and (31) hold.

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

$$\mathbb{E}_t[R^e_{i,t+1}]=\frac{\tau_x\beta^p_{i,t}-\tau_p\beta^x_{i,t}}{\nu_p\tau_x-\nu_x\tau_p}\lambda^M_t+\frac{\nu_p\beta^x_{i,t}-\nu_x\beta^p_{i,t}}{\nu_p\tau_x-\nu_x\tau_p}\lambda^\theta_t \tag{47}$$

and match coefficients in terms of $\beta^x_{i,t}$ and $\beta^p_{i,t}$ with (41), implying

$$\begin{aligned}\lambda^x(\nu_p\tau_x-\nu_x\tau_p) &= \nu_p\lambda^\theta_t-\tau_p\lambda^M_t\\ \lambda^p_t(\nu_p\tau_x-\nu_x\tau_p) &= \tau_x\lambda^M_t-\nu_x\lambda^\theta_t.\end{aligned}$$

Solving for λ^θ_t and λ^M_t confirms (32).

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

$$\begin{aligned}\beta^{CAPM}_{i,t} &= \frac{\mathrm{Cov}_t\left(R^e_{i,t+1},R^e_{M,t+1}\right)}{\mathrm{Var}_t\left(R^e_{M,t+1}\right)}\\ &= \frac{\nu_x\mathrm{Cov}_t\left(R^e_{i,t+1},\sigma_x\varepsilon^x_{t+1}\right)+\nu_p\mathrm{Cov}_t\left(R^e_{i,t+1},\sigma_p\varepsilon^p_{t+1}\right)}{\mathrm{Var}_t\left(R^e_{M,t+1}\right)}=\frac{\nu_x\sigma_x^2\beta^x_{i,t}+\nu_p\sigma_p^2\beta^p_{i,t}}{\nu_x^2\sigma_x^2+\nu_p^2\sigma_p^2}.\end{aligned}$$

Notice that the CAPM factor risk premium remains the same in the one-factor or two-factor models, that is, $\lambda^{CAPM}_t=\lambda^M_t=\nu_x\lambda^x+\nu_p\lambda^p_t$. Given the pricing of expected excess returns in terms of independent aggregate risks (41), we can calculate the CAPM mispricing as

$$\alpha^{CAPM}_{i,t}=\beta^x_{i,t}\lambda^x_t+\beta^p_{i,t}\lambda^p_t-\beta^{CAPM}_{i,t}\lambda^{CAPM}_t=\frac{\left(\beta^x_{i,t}\nu_p-\beta^p_{i,t}\nu_x\right)\left(\nu_p\gamma_x-\nu_x\gamma_p\right)\sigma_x^2\sigma_p^2}{\nu_x^2\sigma_x^2+\nu_p^2\sigma_p^2}.$$

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

C. Computational Algorithm

To solve the model numerically, we discretize the state space. All shocks (x, p, z) follow finite states Markov chains according to Rouwenhorst (1995) with 5 states for x, 9 for p, and 11 for z. We create a log-linear grid of 500 points for current employment N in the interval $[0.01, 20]$. The lower and upper bounds of N are set such that the optimal policies are not binding in the simulation. The choice variable N' is a vector containing 5,000 elements, also log-linearly spaced on the same interval as N. The space of labor market tightness θ is discretized into a linear grid in the interval $[0.1, 1.5]$ with 50 points. The upper and lower bounds for θ are chosen such that the simulated path of equilibrium labor market tightness never steps outside its bounds.

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

1. Initial guess: Make an initial guess for the coefficient vector $\tau = (\tau_0, \tau_\theta, \tau_x, \tau_p)$ of the law of motion (23). We start from $\tau = (-0.0091, 0.98, 0, 0)$ because labor market tightness tends to be highly persistent and in steady state $\tau_0 = (1 - \tau_\theta)\log(\theta^{ss}) = (1 - 0.98)\log(0.634)$.

2. Optimization: Solve the firm's optimization problem (19) given the forecasting rule coefficients τ. We use value function iteration and linear interpolation to obtain the value function off grid points. Given the discretized state space $\Omega = (N, z, x, p, \theta)$ and proportional hiring and firing costs, the firm value function solves

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

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

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

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

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

and S^i is the value of an inactive firm

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

3. Simulation: Use the firm's optimal employment policies $V(\Omega)$ and $F(\Omega)$ to simulate a panel of 5,000 firms for 5,300 periods. Importantly, we impose labor market equilibrium at each date of the simulation by solving θ as the fixed point in Equation (21). In this way, we obtain a time series of realized equilibrium θ.

4. Update coefficients: Delete the initial 300 periods as burn-in 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 2; continue the outer loop iteration until the τ coefficients have converged.

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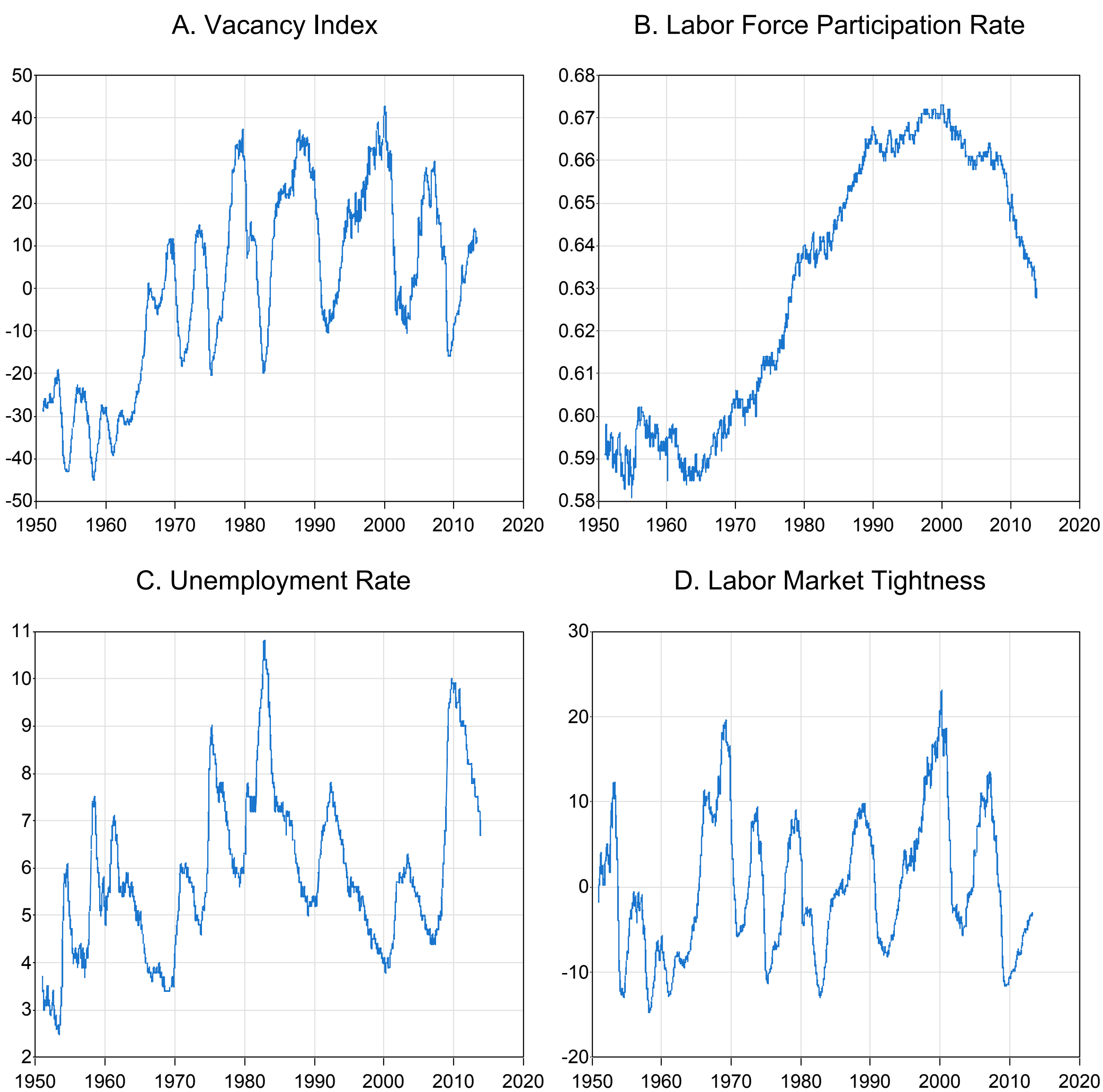

Figure 1. Labor Market Tightness and Its Components

This figure plots the monthly time series of the vacancy index, the labor force participation rate, the unemployment rate, and labor market tightness for the years 1951 to 2012.

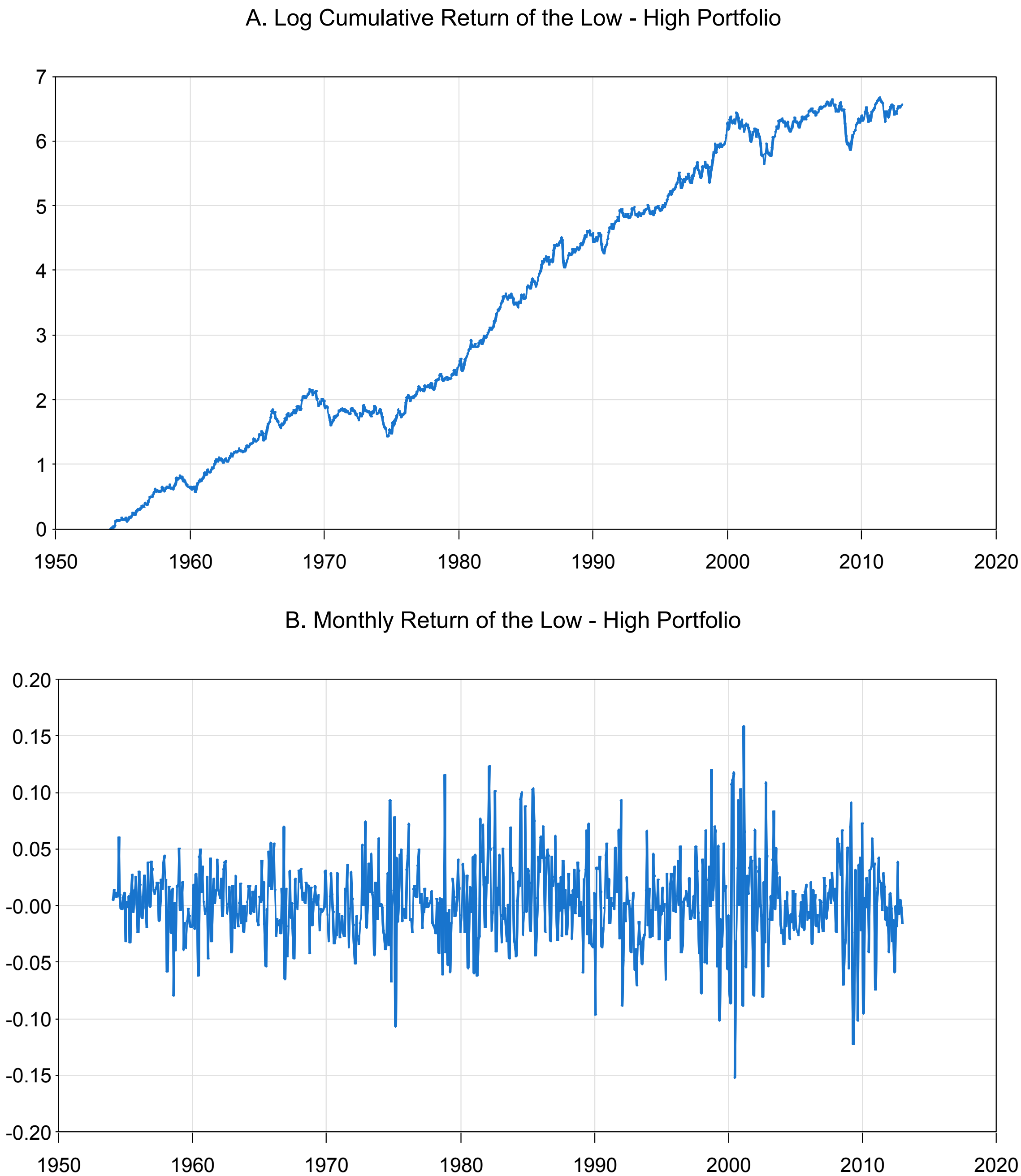

Figure 2. Returns on Long-Short Labor Market Tightness Portfolios
This figure plots the log cumulative (Panel A) and monthly (Panel B) returns on a portfolio that is long the decile of stocks with the lowest exposure to the labor market tightness factor and short the decile of stocks with the highest loadings. The sample spans 1954 to 2012.

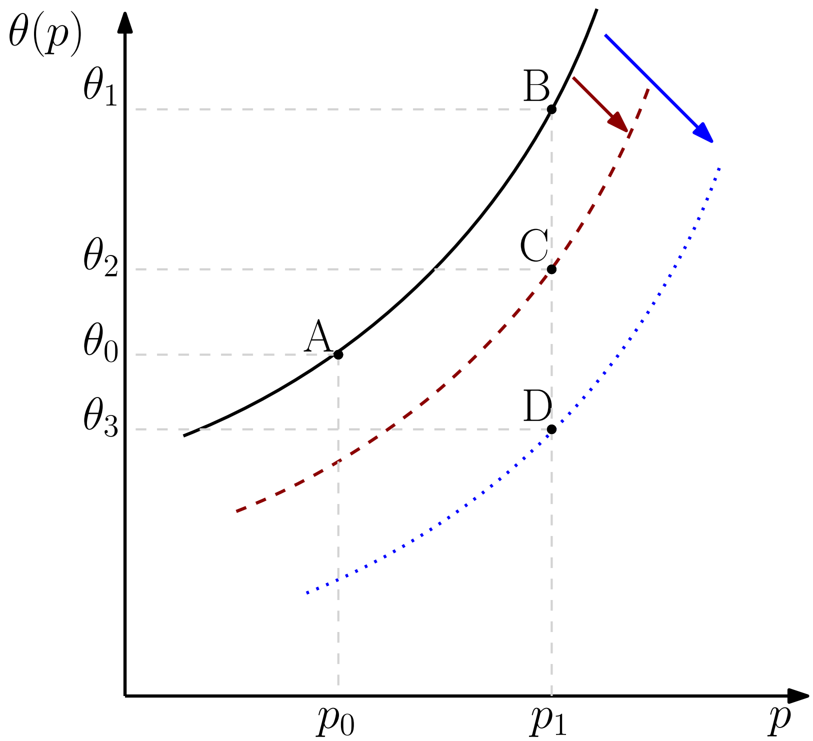

Figure 3. Labor Market Tightness and Matching Efficiency
This figure illustrates the endogenous response of equilibrium labor market tightness $\theta(p)$ to a positive matching efficiency shock p.

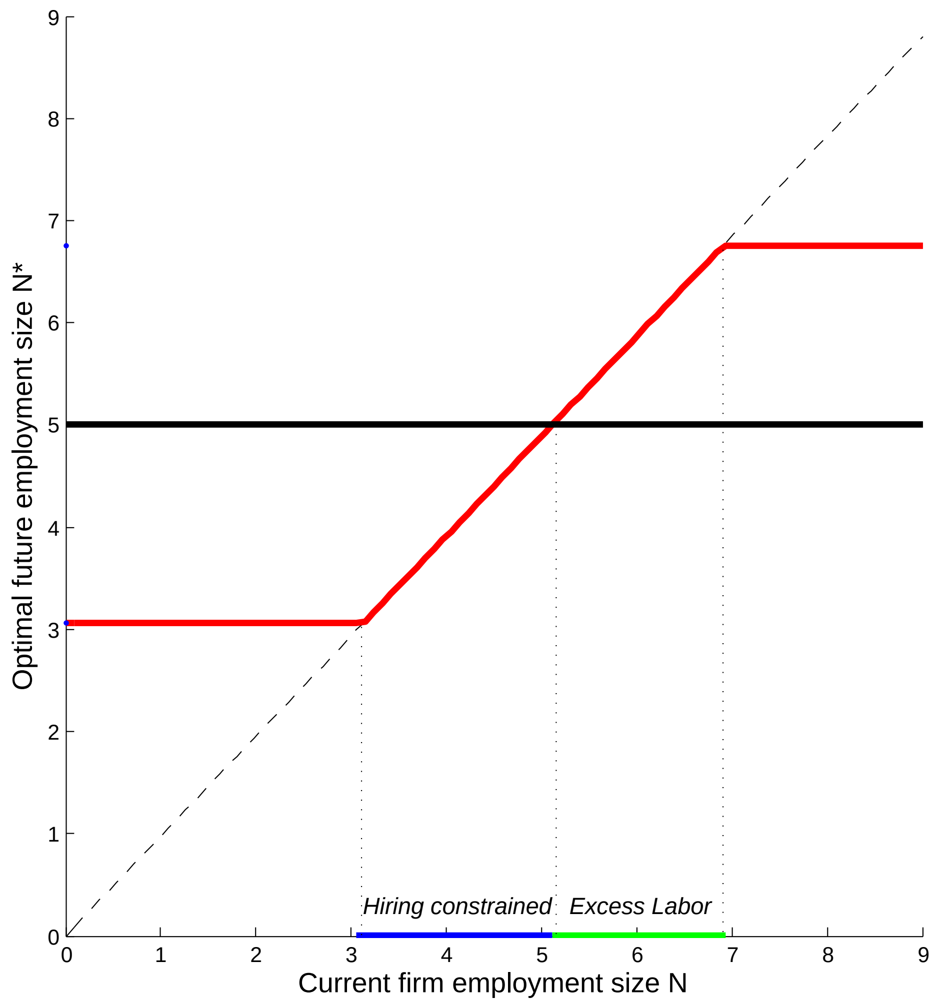

Figure 4. Optimal Employment Policy

This figure illustrates the optimal employment policy. The horizontal black line is the optimal policy when adjusting the workforce is costless. The red kinked curve is the optimal policy in the benchmark model under search frictions. In the middle region, where the optimal policy coincides with the dashed line, firms are inactive. In the inactivity region below the frictionless employment target, firms have too few workers but hiring is too costly (*Hiring constrained*). In the inactivity region above the frictionless employment target, firms have too many workers but firing is too costly (*Excess labor*).

Table I
Summary Statistics

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

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

Table II
Characteristics of Labor Market Tightness Portfolios

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

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

Table III
Performance of Labor Market Tightness Portfolios

This table reports average raw returns and alphas, in percent per month, and loadings from the four-factor model regressions for the ten portfolios of stocks sorted on the basis of their loadings on the labor market tightness factor, as well as for the portfolio that is long the low decile and short the high one. The bottom row gives t-statistics for the low-high portfolio. Firms are assigned into deciles at the end of every month and the value-weighted portfolios are held without rebalancing for 12 months. Conditional alphas are based on either Ferson and Schadt (FS) or Boguth, Carlson, Fisher, and Simutin (BCFS). The sample period is 1954 to 2012.

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

Table IV
Summary Statistics of Risk Factors

This table reports summary statistics for the difference in returns on stocks with low and high loadings β^θ on the labor market tightness factor as well as for the market excess return, and value, size and momentum factors. All data are monthly. Means and standard deviations are in percent. The sample period is 1954 to 2012.

				Correlations			
	Mean	Standard deviation	Sharpe ratio	Low-high β^θ return	Mkt excess return	Value factor	Size factor
Low-high β^θ return	0.47	3.60	0.13				
Market excess return	0.55	4.40	0.13	-0.11			
Value factor	0.38	2.75	0.14	0.08	-0.27		
Size factor	0.20	2.95	0.07	-0.22	0.28	-0.21	
Momentum factor	0.73	4.06	0.12	0.15	-0.13	-0.17	-0.03

Table V
Robustness of Performance of Labor Market Tightness Portfolios

This table reports average raw returns and alphas, in percent per month, four-factor loadings, and corresponding t-statistics for the portfolio that is long the decile of stocks with low loadings on the labor market tightness factor and short the decile with high loadings. In Panel A, firms are assigned into deciles at the end of May and are held for one year starting in July. In Panel B, firms are assigned into deciles at the end of every month τ and are held during month $\tau + 2$. In Panel C, firms are assigned into deciles at the end of every month τ and are held without rebalancing for 12 month beginning in month $\tau + 3$. In Panel D, firms are assigned into quintiles rather than deciles. In Panel E, firms below 20th percentile of NYSE market capitalization are excluded from the sample. In Panel F, the labor market tightness factor is defined as the residual from a time-series regression of log-changes in the labor market tightness on changes in industrial production and the consumer price index, dividend yield, T-Bill rate, term spread, and default spread. In Panel G, labor market tightness factor is defined as the residual from an ARMA(1,1) specification. In Panel H, regression (3) is amended to also include size, value, and momentum factors. Conditional alphas are based on either Ferson and Schadt (FS) or Boguth, Carlson, Fisher, and Simutin (BCFS). In all panels, portfolios are value-weighted. The sample period is 1954 to 2012.

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

Table VI
Fama-MacBeth Regressions of Annual Stock Returns

This table reports the results of annual Fama-MacBeth regressions. Stock returns from July to June are regressed on lagged labor market tightness loadings β^{θ}, market betas β^{M}, log market equity ME, log of the ratio of book equity to market equity BM, 12-month stock return RU, hiring rates HN, investment rates IK, and asset growth rates AG. Reported are average coefficients and the corresponding Newey and West (1987) t-statistics. Details of variable definitions are in Appendix A. The sample period is 1960 to 2012.

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

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

This table reports in Panel A average raw returns and alphas, in percent per month, and loadings from the four-factor model regressions for the ten portfolios of stocks sorted within each of the 48 Ken French-defined industries on the basis of their loadings on the labor market tightness factor. Panel B repeats the analysis for the ten portfolios obtained by sorting 48 value-weighted industry portfolios from Ken French's data library on the basis of their loadings on the labor market tightness factor. The table also shows returns, alphas, and loadings for the portfolio that is long the low decile and short the high one. The bottom row of each panel gives t-statistics for the low-high portfolio. Firms (in Panel A) or industries (in Panel B) are assigned into deciles at the end of every month and are held without rebalancing for twelve months. Conditional alphas are based on either Ferson and Schadt (FS) or Boguth, Carlson, Fisher, and Simutin (BCFS). The sample period is 1954 to 2012.

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

Table VIII
Benchmark Parameter Calibration

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

Parameter	Symbol	Value
Labor Market		
Size of the labor force	L	1.63
Matching function elasticity	ξ	1.27
Bargaining power of workers	η	0.125
Benefit of being unemployed	b	0.71
Returns to scale of labor	α	0.735
Workers quit rate	s	0.022
Flow cost of vacancy posting	κ_h	0.75
Flow cost of firing	κ_f	0.35
Fixed operating costs	f	0.226
Shocks		
Persistence of aggregate productivity shock	ρ_x	0.9830
Volatility of aggregate productivity shock	σ_x	0.005
Persistence of matching efficiency shock	ρ_p	0.9583
Volatility of matching efficiency shock	σ_p	0.025
Persistence of idiosyncratic productivity shock	ρ_z	0.965
Volatility of idiosyncratic productivity shock	σ_z	0.095
Pricing Kernel		
Time discount rate	β	0.994
Price of risk of aggregate productivity shock	γ_x	1
Constant price of risk of matching efficiency shock	$\gamma_{p,0}$	-4.7
Time-varying price of risk of matching efficiency shock	$\gamma_{p,1}$	3.6
Interest rate sensitivity	ϕ	-0.0214

Table IX
Aggregate and Firm-Specific Moments

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

Moment	Data	Model
Aggregate Labor Market		
Unemployment rate	0.058	0.058
Hiring rate	0.036	0.036
Layoff rate	0.014	0.014
Job creation rate	0.026	0.028
Job destruction rate	0.025	0.027
Labor market tightness (LMT)	0.634	0.650
Correlation of LMT and vacancy	0.780	0.747
Correlation of LMT and unemployment rate	-0.830	-0.851
Correlation of unemployment rate and vacancy	-0.360	-0.328
Labor share of income	0.717	0.717
Volatility of aggregate wages to aggregate output	0.520	0.547
Aggregate profits to aggregate output	0.110	0.106
Firm-Level Employment		
Volatility of annual employment growth rates	0.236	0.239
Fraction of firms with zero annual employment growth rates	0.097	0.099
Asset Prices		
Average risk-free rate	0.010	0.010
Volatility of risk-free rate	0.021	0.021
Average market return	0.081	0.082
Stock market volatility	0.176	0.172

Table X
Labor Market Tightness Portfolios from the Benchmark Model

This table compares the performance of the benchmark model with the data. Reported are loadings on labor market tightness factor, β^{θ}, average returns of portfolios sorted by loadings on labor market tightness, alphas from the one-factor CAPM, α^{CAPM}, and cash flow correlations of profits and labor market tightness, Corr. Returns and alphas are expressed in percent per month.

	Data				Model			
Decile	β^{θ}	Return	α^{CAPM}	Corr	β^{θ}	Return	α^{CAPM}	Corr
Low	-0.74	1.10	0.09	-0.13	-0.98	1.10	0.23	-0.12
2	-0.39	1.06	0.10	-0.03	-0.76	1.02	0.19	-0.10
3	-0.23	1.01	0.08	-0.01	-0.64	0.99	0.16	-0.09
4	-0.12	0.99	0.08	-0.09	-0.52	0.95	0.15	-0.09
5	-0.03	0.97	0.06	-0.01	-0.37	0.91	0.13	-0.05
6	0.06	0.99	0.08	-0.00	-0.30	0.90	0.12	-0.04
7	0.16	0.93	0.01	0.10	-0.10	0.85	0.00	-0.01
8	0.28	0.92	-0.01	0.05	0.02	0.83	-0.01	0.09
9	0.45	0.91	-0.06	0.05	0.26	0.79	-0.04	0.11
High	0.85	0.73	-0.27	0.19	0.66	0.72	-0.08	0.15
Low-High	-1.59	0.37	0.36	-0.32	-1.64	0.38	0.31	0.27

Table XI
Labor Market Tightness Portfolios from Alternative Calibrations

This table summarizes average returns of portfolios sorted by loadings on labor market tightness from alternative calibrations. In specification (1), the aggregate productivity shock is not priced, $\gamma_x = 0$. In specification (2), the matching efficiency shock is not priced, $\gamma_{p,0} = 0$, and in specification (3), $\gamma_{p,1} = 0$ so that the aggregate matching efficiency shock has a constant price of risk. In specification (4), the bargaining power of workers, η, is raised by 10% relative to the benchmark calibration. In specifications (5, 6, 7), the costs of laying off workers, κ_f, the vacancy posting cost κ_h, and the fixed operating costs, f, are lowered by 10%, respectively.

Decile	(1) γ_x	(2) $\gamma_{p,0}$	(3) $\gamma_{p,1}$	(4) η	(5) κ_f	(6) κ_h	(7) f
Low	1.09	0.70	0.80	1.10	1.09	1.07	1.05
2	1.03	0.76	0.76	1.02	1.02	1.01	0.99
3	1.00	0.75	0.76	1.00	0.99	0.99	0.98
4	0.96	0.83	0.74	0.96	0.96	0.95	0.95
5	0.91	0.80	0.73	0.92	0.92	0.92	0.92
6	0.91	0.79	0.73	0.92	0.92	0.92	0.92
7	0.86	0.89	0.69	0.85	0.85	0.85	0.86
8	0.85	0.87	0.69	0.84	0.84	0.85	0.85
9	0.79	0.84	0.66	0.78	0.79	0.79	0.79
High	0.73	0.88	0.62	0.72	0.72	0.73	0.73
Low-High	0.36	-0.18	0.18	0.38	0.37	0.34	0.32

Table XII
Forecasting Economic Activity with Labor Market Tightness

This table summarizes the ability of labor market tightness to forecast future economic activity. The quarterly time series for the Gross Domestic Product, Wages and Salary Accruals, and Personal Dividend Income are from the National Income and Product Accounts and total factor productivity from Fernald (2012). The table reports coefficients on labor market tightness growth, their t-statistics, and adjusted R^2 values from bivariate regressions of output growth (Panel A), wage growth (Panel B), and dividend growth (Panel C) on labor market tightness growth and total factor productivity. Forecasting horizons range from one quarter to one year and the data cover the years 1951 to 2012.

	Data				Model			
Horizon (quarters)	1	2	3	4	1	2	3	4
A. Predicting aggregate output growth								
ϑ	0.032	0.040	0.037	0.022	0.041	0.052	0.052	0.047
t-statistic	[7.03]	[5.15]	[3.46]	[1.67]				
R^2	25.13	20.47	14.01	8.59	25.12	11.14	5.94	3.46
B. Predicting aggregate wage growth								
ϑ	0.043	0.063	0.077	0.076	0.046	0.056	0.056	0.052
t-statistic	[9.71]	[8.26]	[7.24]	[5.50]				
R^2	37.80	34.07	30.74	23.97	32.94	16.03	9.45	5.91
C. Predicting aggregate dividend growth								
ϑ	0.078	0.151	0.193	0.199	0.282	0.346	0.324	0.297
t-statistic	[3.81]	[4.99]	[4.69]	[3.88]				
R^2	8.08	14.29	13.89	10.86	23.09	12.59	7.19	4.39

Internet Appendix to A Labor Capital Asset Pricing Model

In this Internet Appendix, we evaluate robustness of the inverse relation between stock return loadings on changes in labor market tightness and future equity returns. We also provide additional empirical results.

A. Controlling for Liquidity and Profitability Factors

Pastor and Stambaugh (2003) show that stocks with higher liquidity risk earn higher returns, and Novy-Marx (2013) documents that more profitable firms generate superior future stock returns. To ensure that our results are not driven by liquidity or profitability risks, we repeat the portfolio analysis of Table III, while controlling for these two sources of risk. As before, we assign stocks into deciles conditional on their loadings on the labor market tightness factor and obtain a monthly time series of future returns for each of the resulting ten portfolios. We use the same models as before to calculate unconditional and conditional alphas, but include the liquidity (Panel A) or profitability factor (Panel B) as an additional regressor in Table IA.I.[17]

The table shows that our results are robust to controlling for the liquidity and profitability factors. The negative relation between labor market tightness loadings and future stock returns is economically important and statistically significant in all regressions. The differences in future returns of portfolios with low and high loadings range from 0.33% to 0.47% monthly.

B. Post-Ranking Loadings on Labor Market Tightness

Table IA.II summarizes post-ranking β^{θ} loadings of the labor market tightness portfolios. For each portfolio, we obtain monthly time series of returns from January 1954 until December 2012. We then regress excess returns of each group annually on the market and the labor market tightness factors, including two Dimson (1979) lags to account for any effects due to non-synchronous trading. We average betas across years to obtain average β^{θ} loadings

[17] Liquidity and profitability factors are from http://faculty.chicagobooth.edu/lubos.pastor/research/ and http://rnm.simon.rochester.edu/data_lib/index.html, respectively. The data on the two factors are available starting only in 1960s, which shortens our sample by as much as 14 years.

for each portfolio. We show results for decile sorts in Panel A and quintile ones in Panel B. The differences in post-ranking betas of the bottom and top groups are sizable, although muted relative to the spread in betas shown in Table II. Importantly, in both panels a positive relation emerges between pre-ranking and post-ranking betas.

C. Controlling for Market Beta

In Table IA.III, we evaluate the relation between β^{θ} loadings and future equity returns, conditional on market betas β^{M}. We sort firms into quintiles based on their β^{θ} and β^{M} loadings computed at the end of month τ and hold the resulting 25 value-weighted portfolios without rebalancing for 12 months beginning in month $\tau + 2$. Table IA.III 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.

D. Controlling for Components of Labor Market Tightness and for Industrial Production

Labor market tightness is composed of three components: vacancy index, unemployment rate, and labor force participation rate. The negative relation between labor market tightness loadings and future stock returns can plausibly be driven by just one of these components, rather than the combination of them, that is the labor market tightness. It could also be driven by changes in industrial production, with which labor market tightness is highly correlated (see Table I). To explore whether this is the case, we first estimate loadings from a two-factor regression of stock excess returns on market excess returns and log changes in either the vacancy index (β^{Vac}), the unemployment rate (β^{Unemp}), the labor force participation rate (β^{LFPR}), or the industrial production (β^{IP}). Following the methodology used in the main body of the paper, we next study future performance of portfolios formed on the basis of these loadings and also run Fama-MacBeth regressions of annual stock returns on the lagged loadings and control variables. Tables IA.IV and IA.V show that none of the considered loadings relate robustly to future equity returns. Loadings on the vacancy factor relate negatively but weakly to future stock returns, and loadings on the unemployment rate factor relate positively but also weakly. There is no convincing evidence that loadings on either the labor force participation factor or the industrial production factor relate to future returns. Overall, the results suggest that the inverse relation between labor market tightness loadings and future stock returns is not driven by vacancies, unemployment rates, or labor force participation rates alone, but rather by their interaction: the labor market tightness.

E. Loadings on 48 Industry Portfolios

In Table IA.VI, we summarize labor market tightness statistics for the 48 value-weighted industry portfolios from Ken French's data library. We report average conditional betas from rolling three-year regressions, their corresponding standard deviations, and the fractions of months an industry falls into the high or the low β^{θ} quintiles. Differences in loadings on labor market tightness across industries are small, with average conditional betas falling in a tight range from -0.097 (Precious Metals) to 0.071 (Real Estate). All industries exhibit significant time variation in β^{θ}, suggesting that industry return sensitivities to changes in labor market tightness vary strongly over time, conceivably in response to changes in the underlying economics of the industry. For example, the Precious Metals industry has the lowest average conditional loading but it still falls in the top β^{θ} quintile 21% of the time. Overall, the results suggest considerable heterogeneity and time variation in loadings on labor market tightness across industries.

Table IA.I
Performance of Labor Market Tightness Portfolios: Controlling for Liquidity and Profitability Factors

This table reports average raw returns and alphas, in percent per month, and five-factor betas 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 one. In Panel A, all alphas are computed by including the Pastor-Stambaugh liquidity factor (LIQ). In Panel B, all alphas are computed by including the Novy-Marx profitability factor (PMU). The bottom row of each Panel gives t-statistics for the low-high portfolio. Firms are assigned into deciles at the end of every month and the value-weighted portfolios are held without rebalancing for 12 months. Conditional alphas are based on either Ferson and Schadt (FS) or Boguth, Carlson, Fisher, and Simutin (BCFS). The sample period is January 1968 to December 2012 in Panel A, and July 1963 to December 2012 in Panel B.

A. Controlling for Pastor-Stambaugh liquidity factor

	Raw	Uncond. Alphas: Liquidity +			Cond. Alphas		5-Factor Loadings				
Decile	Return	Market	3-Factor	4-Factor	FS	BCFS	MKT	HML	SMB	UMD	LIQ
Low	1.00	0.01	0.05	0.03	0.05	0.05	1.17	-0.14	0.38	0.02	0.02
2	1.03	0.13	0.12	0.13	0.11	0.11	1.05	0.01	-0.02	-0.01	0.04
3	0.97	0.10	0.08	0.10	0.08	0.08	0.99	0.06	-0.09	-0.02	0.03
4	0.96	0.11	0.09	0.09	0.09	0.09	0.97	0.08	-0.12	-0.01	0.03
5	0.92	0.10	0.04	0.03	0.07	0.06	0.96	0.15	-0.11	0.01	0.01
6	0.93	0.11	0.08	0.05	0.09	0.08	0.97	0.10	-0.11	0.03	-0.02
7	0.89	0.08	0.07	0.08	0.06	0.06	0.97	0.04	-0.07	-0.01	-0.06
8	0.87	0.03	0.02	0.07	0.02	0.03	1.01	0.00	0.03	-0.06	-0.08
9	0.73	-0.16	-0.15	-0.09	-0.14	-0.12	1.12	-0.08	0.19	-0.07	-0.10
High	0.53	-0.43	-0.40	-0.32	-0.35	-0.34	1.16	-0.22	0.64	-0.09	-0.12
Low-High	0.47	0.44	0.45	0.34	0.40	0.39	0.01	0.08	-0.25	0.11	0.14
t-statistic	[2.82]	[2.62]	[2.67]	[2.03]	[2.41]	[2.35]	[0.24]	[1.29]	[-4.70]	[2.99]	[3.15]

B. Controlling for Novy-Marx profitability factor

	Raw	Uncond. Alphas: Profitability +			Cond. Alphas		5-Factor Loadings				
Decile	Return	Market	3-Factor	4-Factor	FS	BCFS	MKT	HML	SMB	UMD	PMU
Low	1.05	0.04	0.09	0.07	0.06	0.06	1.17	-0.15	0.39	0.02	-0.10
2	1.03	0.12	0.09	0.09	0.10	0.09	1.05	0.04	-0.01	0.00	0.08
3	0.99	0.12	0.07	0.08	0.10	0.09	1.00	0.09	-0.08	-0.02	0.09
4	0.97	0.11	0.06	0.07	0.10	0.09	0.97	0.10	-0.11	0.00	0.08
5	0.93	0.09	0.00	-0.01	0.07	0.06	0.96	0.17	-0.11	0.01	0.09
6	0.93	0.07	0.01	-0.02	0.06	0.05	0.98	0.13	-0.11	0.03	0.11
7	0.89	0.00	-0.03	-0.03	-0.01	-0.01	0.98	0.07	-0.07	-0.01	0.12
8	0.89	-0.03	-0.06	-0.02	-0.04	-0.02	1.02	0.03	0.02	-0.05	0.12
9	0.77	-0.20	-0.17	-0.10	-0.18	-0.15	1.12	-0.10	0.17	-0.07	-0.04
High	0.59	-0.42	-0.35	-0.26	-0.37	-0.36	1.16	-0.29	0.64	-0.09	-0.22
Low-High	0.45	0.47	0.44	0.33	0.43	0.42	0.02	0.13	-0.25	0.12	0.13
t-statistic	[2.91]	[2.96]	[2.78]	[2.05]	[2.77]	[2.67]	[0.46]	[2.25]	[-4.86]	[3.26]	[1.80]

Table IA.II
Post-Ranking Betas of Labor Market Tightness Portfolios

This table reports post-ranking β^θ loadings of the labor market tightness portfolios. Firms are assigned into deciles by β^θ at the end of every month and the value-weighted portfolios are held without rebalancing for 12 months. Excess returns of each portfolio are then regressed annually on the market and the labor market tightness factors, including two Dimson (1979) lags to account for effects of non-synchronous trading. Betas are averaged across the years to obtain average β^θ loadings for each portfolio. Panel A reports results for decile portfolios, and Panel B for quintile ones. The last column of each Panel shows the differences in post-ranking betas of the bottom and top groups. The sample period is 1954 to 2012.

A. Post-ranking betas of decile portfolios

	Low	2	3	4	5	6	7	8	9	High	Low - High
β^θ	-0.07	-0.13	-0.13	-0.01	0.00	-0.06	0.13	0.04	0.15	0.18	-0.25

B. Post-ranking betas of quintile portfolios

	Low	2	3	4	High	Low - High
β^θ	-0.10	-0.06	-0.01	0.06	0.10	-0.20

Table IA.III
Performance of Portfolios Sorted by Loadings on Market and Labor Market Tightness Factors

This table reports average excess returns, in percent per month, for the quintile portfolios of stocks sorted on the basis of their loadings on 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 and the value-weighted portfolios are held without rebalancing for 12 months. The bottom row and the last column of each Panel give t-statistics for the low-high portfolios. The sample period is 1954 to 2012.

	Low β^M	2	3	4	High β^M	Low-High β^M	
A. Independent sorts							
Low β^θ	0.62	0.64	0.51	0.47	0.30	0.32	[1.79]
2	0.64	0.54	0.54	0.39	0.23	0.41	[2.53]
3	0.58	0.56	0.47	0.34	0.13	0.45	[2.69]
4	0.61	0.51	0.42	0.25	0.20	0.41	[2.43]
High β^θ	0.28	0.34	0.17	0.11	-0.03	0.31	[1.69]
Low-High β^θ	0.34	0.29	0.34	0.36	0.33		
t-statistic	[2.27]	[2.31]	[2.61]	[2.73]	[2.60]		
B. Conditional sorts: first on β^θ, then on β^M							
Low β^θ	0.63	0.60	0.44	0.39	0.30	0.33	[1.78]
2	0.64	0.56	0.56	0.44	0.31	0.33	[2.23]
3	0.59	0.59	0.47	0.38	0.21	0.39	[2.66]
4	0.62	0.53	0.38	0.29	0.17	0.45	[2.86]
High β^θ	0.31	0.31	0.04	0.04	-0.04	0.35	[1.80]
Low-High β^θ	0.32	0.29	0.40	0.35	0.34		
t-statistic	[2.21]	[2.32]	[2.95]	[2.64]	[2.49]		
C. Conditional sorts: first on β^M, then on β^θ							
Low β^θ	0.70	0.60	0.51	0.44	0.27	0.43	[2.34]
2	0.63	0.53	0.55	0.41	0.19	0.44	[2.61]
3	0.53	0.54	0.45	0.32	0.18	0.35	[2.03]
4	0.62	0.53	0.44	0.22	0.14	0.48	[2.79]
High β^θ	0.32	0.39	0.24	0.10	-0.16	0.49	[2.39]
Low-High β^θ	0.37	0.21	0.26	0.34	0.43		
t-statistic	[2.70]	[1.91]	[2.24]	[2.53]	[2.95]		

Table IA.IV
Performance of Portfolios Sorted by Loadings on Components of Labor Market Tightness and Industrial Production

This table reports four-factor alphas, in percent per month, for the ten portfolios of stocks sorted on the basis of β^{Vac}, β^{Unemp}, β^{LFPR}, and β^{IP}, which are loadings from two-factor regressions of stock excess returns on market excess returns and log changes in either the vacancy index, the unemployment rate, the labor force participation rate, or industrial production, respectively. The bottom two rows show the alphas and the corresponding t-statistics for the portfolio that is long the low decile and short the high one. Firms are assigned into groups at the end of every month and the value-weighted portfolios are held without rebalancing for 12 months. The sample period is 1954 to 2012.

	Four-factor alphas of portfolios sorted by			
Decile	β^{Vac}	β^{Unemp}	β^{LFPR}	β^{IP}
Low	0.02	-0.22	-0.05	-0.07
2	0.12	-0.08	-0.02	0.07
3	0.11	0.01	0.02	0.04
4	0.02	0.02	0.03	0.10
5	0.02	0.11	0.03	0.05
6	0.01	0.11	0.04	0.04
7	0.10	0.04	0.04	0.02
8	0.02	0.09	0.08	-0.07
9	-0.05	0.13	0.10	-0.07
High	-0.22	-0.01	0.08	-0.07
Low-High	0.24	-0.20	-0.13	-0.01
t-statistic	[1.58]	[-1.33]	[-0.89]	[-0.06]

Table IA.V
Fama-MacBeth Regressions of Annual Stock Returns

This table reports the results of annual Fama-MacBeth regressions. Stock returns from July to June are regressed on lagged market betas (β^M) and 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 index, or industrial production (β^{LFPR}, β^{Unemp}, β^{Vac}, or β^{IP}, respectively). Regressions (7) to (12) also control for log market equity, log of the ratio of book equity to market equity, 12-month stock return, hiring rates, investment rates, and asset growth rates. Reported are average coefficients and the corresponding Newey and West (1987) t-statistics. Details of variable definitions are in Appendix A. The sample period is 1960 to 2012.

Reg	β^M	β^{LFPR}	β^{Unemp}	β^{Vac}	β^{IP}	Controls
(1)	0.001	0.001				No
	[0.04]	[1.19]				
(2)	0.000		0.011			No
	[-0.01]		[1.51]			
(3)	0.001			-0.007		No
	[0.05]			[-1.13]		
(4)	0.001				-0.001	No
	[0.09]				[-0.43]	
(5)	0.000	0.001	0.015	0.002		No
	[-0.00]	[1.08]	[1.51]	[0.35]		
(6)	0.001	0.001	0.015	0.004	0.000	No
	[0.05]	[1.35]	[1.15]	[0.48]	[-0.10]	
(7)	0.012	0.001				Yes
	[0.86]	[1.54]				
(8)	0.011		0.021			Yes
	[0.81]		[2.21]			
(9)	0.011			-0.024		Yes
	[0.77]			[-3.36]		
(10)	0.012				-0.004	Yes
	[0.86]				[-1.04]	
(11)	0.011	0.001	0.012	-0.017		Yes
	[0.79]	[1.21]	[1.14]	[-1.25]		
(12)	0.012	0.001	0.012	-0.015	0.000	Yes
	[0.86]	[1.34]	[0.96]	[-1.06]	[-0.11]	

Table IA.VI
Loadings of 48 Industry Portfolios on Labor Market Tightness

This table reports average and standard deviation of conditional loadings on the labor market tightness factor for industry portfolios. Loadings are computed as in regression (3), based on rolling three-year windows. The last two columns show the fraction of months each industry was assigned to the low and high β^θ quintiles. Definitions of the 48 industries are from Ken French's data library. The sample period is 1954 to 2012 for all industries except Candy & Soda (1963 to 2012), Defense (1963 to 2012), Fabricated Products (1963 to 2012), Healthcare (1969 to 2012), and Precious Metals (1963 to 2012).

			Fraction of months in	
Industry	Average cond β^θ	Standard dev of β^θ	low β^θ quintile	high β^θ quintile
Precious Metals	-0.097	0.612	0.595	0.211
Tobacco Products	-0.086	0.211	0.416	0.152
Beer & Liquor	-0.063	0.162	0.337	0.060
Utilities	-0.047	0.106	0.271	0.047
Communication	-0.031	0.103	0.123	0.118
Banking	-0.030	0.151	0.287	0.094
Candy & Soda	-0.025	0.187	0.267	0.239
Business Services	-0.023	0.113	0.075	0.079
Food Products	-0.022	0.114	0.213	0.094
Coal	-0.019	0.272	0.355	0.313
Electronic Equipment	-0.019	0.133	0.166	0.152
Shipping Containers	-0.018	0.112	0.137	0.123
Medical Equipment	-0.018	0.155	0.278	0.136
Computers	-0.016	0.175	0.220	0.235
Chemicals	-0.008	0.083	0.073	0.144
Almost Nothing	-0.006	0.220	0.208	0.186
Insurance	0.000	0.133	0.204	0.114
Petroleum and Natural Gas	0.001	0.136	0.220	0.144
Agriculture	0.002	0.206	0.319	0.201
Pharmaceutical Products	0.004	0.128	0.152	0.169
Retail	0.005	0.106	0.069	0.157
Steel Works Etc	0.005	0.149	0.209	0.166
Consumer Goods	0.006	0.093	0.032	0.079
Transportation	0.006	0.120	0.129	0.112
Printing and Publishing	0.007	0.152	0.161	0.220
Construction	0.008	0.173	0.274	0.213
Entertainment	0.010	0.165	0.260	0.209
Fabricated Products	0.011	0.240	0.274	0.277
Personal Services	0.012	0.178	0.202	0.202
Restaraunts, Hotels, Motels	0.013	0.149	0.159	0.233
Trading	0.017	0.113	0.066	0.158
Defense	0.019	0.212	0.284	0.274
Electrical Equipment	0.020	0.093	0.042	0.194
Construction Materials	0.021	0.119	0.065	0.105
Shipbuilding, Railroad Equipment	0.021	0.204	0.262	0.244
Aircraft	0.024	0.128	0.224	0.195
Machinery	0.027	0.103	0.043	0.132
Recreation	0.028	0.247	0.188	0.295
Rubber and Plastic Products	0.031	0.125	0.121	0.216
Business Supplies	0.033	0.119	0.116	0.230
Measuring and Control Equipment	0.036	0.121	0.141	0.230
Apparel	0.038	0.142	0.078	0.190
Healthcare	0.040	0.273	0.297	0.291
Automobiles and Trucks	0.042	0.117	0.069	0.425
Non-Metallic and Industrial Metal Mining	0.042	0.202	0.267	0.258
Wholesale	0.043	0.114	0.026	0.134
Textiles	0.056	0.140	0.073	0.284
Real Estate	0.071	0.195	0.127	0.355