Internet Appendix to:
A Labor Capital Asset Pricing Model*

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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. Robustness to Using Different Beta Estimation Horizons

In the paper, we use three years of monthly data to compute loadings on the labor market tightness factor. We now evaluate robustness of our results to different beta estimation horizons. In Table IA.I, we estimate betas using 24, 48, or 60 months of data and otherwise do not modify our empirical methods. For all considered horizons, the differences in future performance of portfolios with low and high labor market tightness loadings remain economically and statistically significant.

B. 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

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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.II.[1]

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 0.36% to 0.50% monthly.

C. Post-Ranking Loadings on Labor Market Tightness

Table IA.III summarizes pre- and post-ranking β^{θ} loadings of the labor market tightness portfolios computed using four different approaches. To implement the first approach, for each portfolio, we obtain monthly time series of returns from January 1954 until December 2014. 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 for each portfolio. 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.

Generating a spread in post-ranking betas that is similar to the spread in pre-ranking betas is challenging, and many well-regarded studies face this issue. For example, in an empirical setup similar to ours, Ang, Hodrick, Xing, and Zhang (2006) investigate whether loadings on changes in VIX are priced in the cross-section of stocks. The spreads in their pre- and post-ranking betas are 4.27 and 0.051, respectively (p. 268). They note, however, that "Finding large spreads in the next-month post-formation... loadings is a very stringent requirement" (p. 271) and instead calculate loadings on a factor constructed to mimic innovations in market

[1] 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. The data on the profitability factor from Novy-Marx's website ends in 2012, and we extend it through 2014 by following the methodology of Novy-Marx (2013).

volatility. To implement our second approach for computing post-ranking betas, we follow their method, which in turn builds on Breeden, Gibbons, and Litzenberger (1989) and Lamont (2001), and create a factor to mimic innovations in labor market tightness. In particular, we run the regression

$$\vartheta_t = c + b' X_t + u_t,$$

where X_t represents excess returns on the base assets. We use the decile portfolios sorted on past β^θ as the base assets. As Ang, Hodrick, Xing, and Zhang (2006) note on page 270, the coefficient b has the interpretation of weights in a zero-cost portfolio, and the return on the portfolio, $b' X_t$, is the factor that mimics innovations in labor market tightness.

We also consider two other approaches to construct this factor. First, we define it simply as the difference in returns of the decile portfolios with low and high β^θ. Second, we closely follow the approach of Fama and French (1993) and at the end of month t sort stocks into three groups by β_t^θ (Low L, Medium M, or High H), estimated from Equation (3) of the paper. Independently, we also sort stocks into two groups by market capitalizations (Small S or Big B). As in Fama and French (1993), we base the assignments into groups on breakpoints obtained from NYSE stocks only. We use percentiles 30 and 70 when splitting firms into the three β^θ groups, and the median when splitting them by size. We then compute value-weighted returns of each of the six portfolios in month $t+1$. The resulting factor is the average of the two portfolios with low β^θ less the average of the high-β^θ portfolios, $(LS+LB)/2-(HS+HB)/2$.

In Table IA.III, we report pre- and post-ranking betas computed using the four approaches. We find strong evidence of correspondence between pre- and post-ranking betas. The difference in betas of low- and high-β^θ portfolios is always significant. For example, when we follow the Ang, Hodrick, Xing, and Zhang (2006) approach, this difference reaches 1.95 for pre-ranking betas and 3.68 for post-ranking betas. The corresponding numbers that we obtain using the factor based on the methodology of Fama and French (1993) are 0.73 and 1.20. Taken together, the evidence points to a tight relation between pre- and post-ranking betas.

D. Controlling for Market Beta

In Table IA.IV, 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.IV shows that irrespective of whether we consider independent sorts or dependent sorts (e.g., first on β^M and then by β^θ within each market beta quintile), stocks with low loadings on the labor market tightness factor significantly outperform stocks with high loadings.

E. 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.V and IA.VI 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.

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, Porter, 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 inverse 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 IA.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 0.33% ($t = 3.70$) monthly when portfolio assignment is done within industries, whereas the corresponding figure is 0.48% ($t = 3.66$) 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 by their loadings on the labor market tightness factor and study future returns of the resulting decile portfolios.[2] Panel B of Table IA.VII shows that industries with low loadings outperform industries with high loadings by 0.40% per month.

G. Loadings on 48 Industry Portfolios

In Table IA.VIII, 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 -0.090 (Tobacco Products) to 0.074 (Real Estate). All industries exhibit

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

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 Tobacco Products industry has the lowest average conditional loading but it still falls in the top β^{θ} quintile 14% of the time. Overall, the results suggest considerable heterogeneity and time variation in loadings on labor market tightness across industries.

H. Cross-Sectional Dispersion in Labor Market Tightness Loadings

Figure IA.I plots the time series of cross-sectional moments of β^{θ}, highlighting considerable cross-sectional dispersion in estimated loadings.

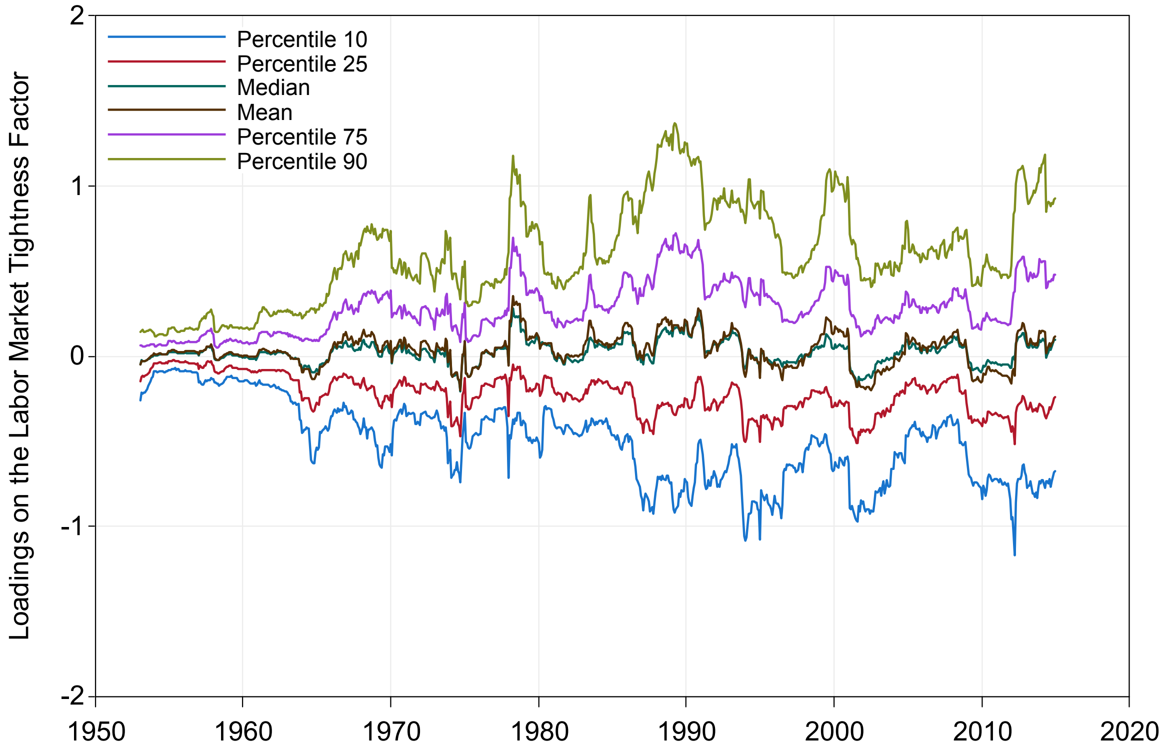


Figure IA.I. Loadings on the Labor Market Tightness Factor. This figure plots cross-sectional moments of the firm-level loadings on the labor market tightness factor for the years 1954 to 2014.

I. Estimating Matching Efficiency Shocks

In this subsection, we follow Lubik (2009) and estimate the matching efficiency shocks as the residuals from a fitted non-linear Beveridge curve of vacancy and unemployment.[3] The goal is to show that our empirical results are qualitatively robust when using these estimated shocks instead of log changes in labor market tightness to calculate loadings.

Aggregating the law of motion of the firm workforce size, equation (9), we obtain the aggregate dynamics of employment

$$\bar{N}_{t+1} = (1-s)\bar{N}_t + \mathcal{M}(\bar{U}_t, \bar{V}_t, p_t) - \bar{F}_t = (1-\hat{s})\bar{N}_t + \frac{e^{p_t}\bar{U}_t\bar{V}_t}{(\bar{U}_t^{\xi} + \bar{V}_t^{\xi})^{\frac{1}{\xi}}}, \tag{1}$$

where $\bar{N}_t$, $\bar{V}_t$, $\bar{U}_t$ denote the aggregate employment, aggregate vacancies, aggregate unemployed searching for jobs, respectively, and $\hat{s}$ is the total separation rate, which is the sum of voluntary quit rate and involuntary separation. To estimate the unknown parameters $(\hat{s}, \xi)$, we derive the steady state Beveridge curve and express the relation in rates.

Specifically, we define rates scaled by the size of the labor force L, such that $n = \frac{\bar{N}}{L}$, $v = \frac{\bar{V}}{L}$, $u = \frac{\bar{U}}{L}$, and obtain the following steady state relation

$$n = (1-\hat{s})n + \frac{uv}{(u^{\xi} + v^{\xi})^{\frac{1}{\xi}}}.$$

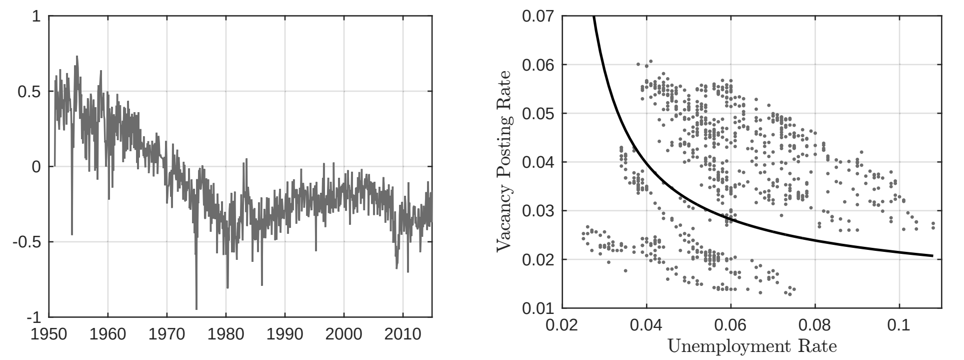
Further derivation gives the steady state Beveridge curve as a non-linear function of the vacancy rate v and unemployment rate u

$$v = \left[\left(\frac{\hat{s}(1-u)}{u}\right)^{-\xi} - 1\right]^{-\frac{1}{\xi}} u.$$

Based on this steady state relation, we can estimate the parameters $(\hat{s}, \xi)$ using non-linear least squares fitting based on the monthly unemployment rate u_t and the monthly vacancy rate v_t such that

$$v_t = \left[\left(\frac{\hat{s}(1-u_t)}{u_t}\right)^{-\xi} - 1\right]^{-\frac{1}{\xi}} u_t + \varepsilon_t.$$

[3] We acknowledge that the estimation exercise here is by no means a perfect recovery of the underlying unobservable matching efficiency shock. First, a structural estimation is model-dependent and it introduces estimation noise. Second, similar to the debates about estimating aggregate TFP shocks, the estimation of matching efficiency shocks might be subject to an endogeneity bias arising from the search behavior of agents on either side of the market (as pointed out by Borowczyk-Martins, Jolivet, and Postel-Vinay (2013), among others).



(a) Estimated Matching Efficiency (b) Empirical vs. Fitted Beveridge Curve

Figure IA.II. Estimated Matching Efficiency Shocks. This figure plots the monthly estimated matching efficiency shocks (left), as well as the empirical and fitted Beveridge Curves for 1951-2014.

The point estimates are $\hat{s} = 0.0167$ and $\xi = 0.7614$, which are highly significant. Plugging these point estimates into equation (1), we can back out the matching efficiency shock from

$$e^{p_t} = ((1 - u_{t+1}) - (1 - \hat{s})(1 - u_t)) \frac{(u_t^{\xi} + v_t^{\xi})^{\frac{1}{\xi}}}{u_t v_t}.$$

Figure IA.II depicts the estimated matching efficiency time series as well as the empirical and the fitted Beveridge curve. In Table IA.IX, we report summary statistics for the estimated monthly matching efficiency shock Δp, as well as its correlations with log changes of LMT, VAC, UNEMP, LFPR, and IP (in the same format as Table I in the paper). The estimated matching efficiency shock is strongly positively correlated with the labor market tightness factor and is more volatile.

Next, we show that the estimated matching efficiency shock is economically consistent with our model in terms of the dynamics for labor market tightness and consumption growth. In the model, we postulate a log-linear functional form to approximate the dynamics for labor market tightness in equation (21). Using log changes in industrial production to proxy for aggregate productivity shocks, we can estimate the data counterpart of the aggregate law of motion for labor market tightness with a regression and obtain

$$\log(\theta_{t+1}) = -0.007 + 0.999 \log(\theta_t) + 3.067 \Delta \log(\mathrm{IP}_{t+1}) + 0.111 \Delta p_{t+1}.$$

All slope coefficients are significant at the 1%-level. Consistent with the model, log labor market tightness is highly persistent and loads positively on both TFP (proxied by industrial production, IP) and matching efficiency shocks.

We have assumed in the model that matching efficiency shocks have a negative price of risk. If we were to build a full-blown general equilibrium model, the endogenously generated consumption growth dynamics should negatively relate to changes in matching efficiency shocks to be consistent with a negative price of risk. To investigate whether this relation holds in the data, we regress consumption growth on the quarterly matching efficiency shocks and the quarterly changes of industrial production (as a proxy for the productivity shocks). We obtain the following OLS estimates:

$$\Delta \log(C_{t+1}) = 0.004 + 0.204 \Delta \log(\mathrm{IP}_{t+1}) - 0.015 \Delta p_{t+1},$$

where all slope coefficients are again significant at the 1%-level. Consistent with the model, consumption growth responds positively to TFP shocks and negatively to matching efficiency shocks.

To test the asset pricing implications of matching efficiency shocks, we follow the same methodology as in the paper by replacing the labor market tightness factor ϑ with changes in matching efficiency Δp. In particular, we compute rolling loadings by regressing stock excess returns on market excess return and matching efficiency shocks. Following the same methods as in the paper, we form decile portfolios on the basis of matching efficiency loadings and study their future returns. The difference in returns between portfolios with low and high matching efficiency loadings averages 2.64% per year. This number is smaller than the corresponding spread in returns of labor market tightness portfolios, but this should not be surprising because estimation of the matching efficiency shocks introduces measurement noise. At the same time, the difference in annual returns of portfolios with low and high efficiency shock loadings is highly correlated (over 50%) with the difference in returns of portfolios with low and high labor market tightness loadings.

Figure IA.III plots log cumulative returns for the low-high matching efficiency loading portfolio. Comparing this figure with Figure 3 in the paper visually confirms and helps to establish that the estimated matching efficiency shock is the main driving force of our return predictability results.

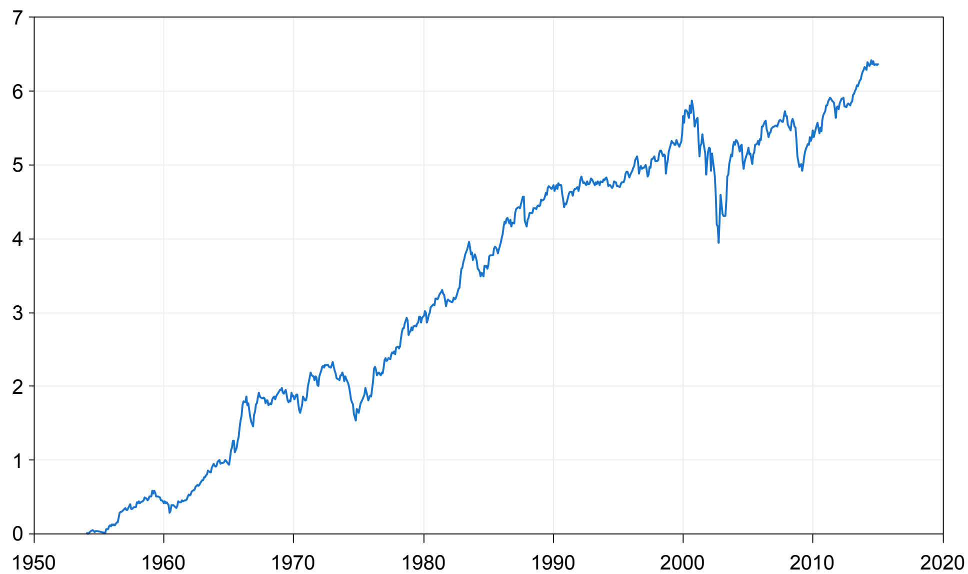


Figure IA.III. Log Cumulative Return of the Low-High Portfolio. This figure plots the log cumulative return of the low-high portfolio sorted by loadings on the estimated matching efficiency shocks.

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Table IA.I
Performance of Labor Market Tightness Portfolios: Robustness to Using Different Beta Estimation Horizons

This table reports average raw returns and alphas, in percent per month, and loadings from the four-factor model regressions for the 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. The loadings are computed from rolling regressions of stock excess returns on market excess returns and the labor market tightness factor, using two, four, or five years of monthly data (Panels A, B, or C, respectively). The t-statistics are in square brackets. 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 2014.

	Raw	Unconditional Alphas			Cond. Alphas		4-Factor Loadings			
Decile	Return	CAPM	3-Factor	4-Factor	FS	BCFS	MKT	HML	SMB	UMD
A. Betas estimated over 24 months										
Low-High	0.35	0.43	0.39	0.38	0.37	0.36	-0.05	0.13	-0.24	0.00
$t-$statistic	[2.63]	[3.16]	[2.88]	[2.78]	[2.80]	[2.71]	[-1.64]	[2.47]	[-5.02]	[0.06]
B. Betas estimated over 48 months										
Low-High	0.36	0.44	0.45	0.32	0.40	0.39	-0.07	0.08	-0.26	0.13
$t-$statistic	[2.68]	[3.34]	[3.40]	[2.41]	[3.07]	[2.98]	[-2.12]	[1.55]	[-5.67]	[4.06]
C. Betas estimated over 60 months										
Low-High	0.28	0.39	0.39	0.27	0.32	0.31	-0.10	0.10	-0.33	0.13
$t-$statistic	[2.07]	[2.55]	[2.58]	[2.02]	[2.15]	[2.08]	[-2.79]	[1.72]	[-6.18]	[3.52]

Table IA.II
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 availability of data on the liquidity and profitability factors limits the sample period from January 1968 to December 2014 in Panel A, and from July 1963 to December 2014 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	0.99	-0.01	0.02	0.01	0.03	0.03	1.17	-0.13	0.43	0.01	0.02
2	1.01	0.12	0.11	0.12	0.10	0.10	1.04	0.02	-0.01	-0.02	0.03
3	0.96	0.09	0.06	0.09	0.07	0.07	1.00	0.08	-0.10	-0.04	0.03
4	0.95	0.10	0.06	0.06	0.07	0.07	0.98	0.10	-0.11	-0.01	0.04
5	0.92	0.09	0.02	0.01	0.06	0.05	0.97	0.16	-0.10	0.01	0.01
6	0.92	0.09	0.05	0.02	0.07	0.06	0.97	0.11	-0.11	0.03	-0.01
7	0.90	0.07	0.06	0.07	0.05	0.05	0.97	0.03	-0.07	-0.01	-0.03
8	0.87	0.00	0.00	0.03	0.00	0.01	1.02	-0.01	0.06	-0.04	-0.04
9	0.77	-0.13	-0.11	-0.07	-0.10	-0.08	1.11	-0.10	0.22	-0.05	-0.08
High	0.49	-0.48	-0.47	-0.37	-0.41	-0.40	1.18	-0.18	0.66	-0.11	-0.12
Low-High	0.50	0.47	0.49	0.38	0.44	0.43	-0.01	0.05	-0.23	0.12	0.14
t-statistic	[2.99]	[2.84]	[2.93]	[2.25]	[2.70]	[2.63]	[-0.34]	[0.92]	[-4.24]	[3.18]	[3.16]

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	1.08	0.03	0.08	0.07	0.04	0.04	1.16	-0.15	0.43	0.01	-0.14
2	1.05	0.10	0.08	0.09	0.08	0.08	1.04	0.04	0.00	-0.01	0.05
3	1.02	0.11	0.05	0.09	0.08	0.08	1.00	0.10	-0.08	-0.03	0.08
4	0.99	0.11	0.06	0.06	0.10	0.09	0.97	0.11	-0.10	-0.01	0.04
5	0.96	0.10	0.01	0.00	0.07	0.06	0.97	0.17	-0.10	0.01	0.05
6	0.95	0.07	0.02	-0.01	0.06	0.05	0.97	0.13	-0.11	0.03	0.07
7	0.92	0.02	-0.01	0.01	0.01	0.01	0.97	0.05	-0.07	-0.01	0.07
8	0.93	-0.02	-0.03	0.01	-0.02	0.00	1.03	-0.01	0.05	-0.04	0.03
9	0.84	-0.15	-0.10	-0.05	-0.12	-0.10	1.11	-0.14	0.20	-0.06	-0.11
High	0.60	-0.46	-0.39	-0.29	-0.42	-0.40	1.17	-0.27	0.66	-0.11	-0.28
Low-High	0.47	0.49	0.47	0.36	0.46	0.44	-0.01	0.12	-0.23	0.12	0.15
t-statistic	[3.15]	[3.23]	[3.06]	[2.29]	[3.09]	[2.96]	[-0.21]	[2.04]	[-4.60]	[3.48]	[2.13]

Table IA.III
Pre- and Post-Ranking Betas of Labor Market Tightness Portfolios

This table reports pre- and post-ranking β^{θ} loadings of the labor market tightness portfolios. Pre-ranking β^{θ} are computed as in Table II. To compute post-ranking β^{θ}, excess returns of each decile portfolio are 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. The remaining columns (β^{θ}_{F1} through β^{θ}_{F3}) compute betas with respect to three versions of the factor constructed to mimic innovations in labor market tightness. Factor $F1$ is constructed from the regression of changes in labor market tightness on excess returns of base assets, $\vartheta_t = c + b'X_t + u_t$. Base assets are the decile portfolios sorted on past β^{θ}, and factor $F1$ is the return $b'X_t$. Factor $F2$ is the difference in returns of the decile portfolios with low and high β^{θ}. To construct factor $F3$, at the end of month t stocks are sorted into three groups by β^{θ}_t (Low L, Medium M, or High H), estimated from Equation (3) of the paper. Independently, stocks are also sorted into two groups by market capitalizations (Small S or Big B). Assignments into groups are based on on breakpoints obtained from NYSE stocks only. Percentiles 30 and 70 are used when splitting firms into the three β^{θ} groups, and the median is used when splitting them by size. Value-weighted returns of each of the six portfolios is then computed in month $t+1$. The resulting factor $F3$ is the average of the two portfolios with low β^{θ} less the average of the high-β^{θ} portfolios, $(LS + LB)/2 - (HS + HB)/2$. The sample period is 1954 to 2014.

	Pre-ranking				Post-ranking			
Decile	β^{θ}	β^{θ}_{F1}	β^{θ}_{F2}	β^{θ}_{F3}	β^{θ}	β^{θ}_{F1}	β^{θ}_{F2}	β^{θ}_{F3}
Low	-0.80	-0.77	-0.08	-0.13	-0.03	-1.32	-0.32	-0.44
2	-0.38	-0.46	-0.07	-0.18	-0.08	-1.09	-0.27	-0.51
3	-0.23	-0.35	-0.05	-0.17	-0.02	-0.93	-0.16	-0.37
4	-0.12	-0.24	-0.04	-0.12	0.00	-0.89	-0.09	-0.19
5	-0.02	-0.17	-0.04	-0.08	0.00	0.03	-0.07	-0.12
6	0.06	-0.01	0.00	-0.01	0.01	0.49	-0.04	-0.02
7	0.16	0.09	0.02	0.10	0.03	0.34	0.08	0.22
8	0.28	0.22	0.07	0.18	-0.01	0.87	0.19	0.46
9	0.46	0.56	0.15	0.32	0.07	1.54	0.34	0.64
High	0.92	1.18	0.32	0.60	0.18	2.36	0.68	0.76
High-Low	1.72	1.95	0.40	0.73	0.21	3.68	1.00	1.20
t-statistic	[13.49]	[3.23]	[3.47]	[3.55]	[2.44]	[23.29]	[–]	[21.75]

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

This table reports market model alphas, 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 2014.

	Low β^M	2	3	4	High β^M	Low-High β^M	
A. Independent sorts							
Low β^θ	0.27	0.20	0.13	0.06	-0.13	0.40	[2.26]
2	0.21	0.16	0.14	0.00	-0.19	0.40	[2.53]
3	0.22	0.17	0.07	-0.10	-0.29	0.51	[3.14]
4	0.24	0.13	0.03	-0.15	-0.20	0.44	[2.65]
High β^θ	-0.04	-0.04	-0.18	-0.31	-0.45	0.41	[2.26]
Low-High β^θ	0.30	0.24	0.31	0.38	0.32		
t-statistic	[2.20]	[1.95]	[2.55]	[2.87]	[2.58]		
B. Conditional sorts: first on β^θ, then on β^M							
Low β^θ	0.22	0.19	0.05	0.00	-0.15	0.36	[1.98]
2	0.23	0.17	0.16	0.06	-0.13	0.36	[2.43]
3	0.24	0.19	0.09	-0.04	-0.22	0.46	[3.23]
4	0.27	0.14	-0.01	-0.12	-0.22	0.49	[3.16]
High β^θ	-0.07	-0.06	-0.31	-0.38	-0.47	0.40	[2.07]
Low-High β^θ	0.29	0.25	0.36	0.38	0.32		
t-statistic	[2.20]	[2.06]	[2.87]	[2.84]	[2.45]		
C. Conditional sorts: first on β^M, then on β^θ							
Low β^θ	0.30	0.22	0.15	0.04	-0.18	0.48	[2.66]
2	0.24	0.13	0.14	0.01	-0.20	0.44	[2.68]
3	0.17	0.16	0.05	-0.11	-0.25	0.42	[2.56]
4	0.23	0.13	0.06	-0.17	-0.28	0.51	[2.98]
High β^θ	0.03	0.03	-0.15	-0.32	-0.60	0.64	[3.27]
Low-High β^θ	0.27	0.17	0.29	0.36	0.42		
t-statistic	[2.10]	[1.95]	[2.56]	[2.75]	[3.01]		

Table IA.V

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 2014.

	Four-factor alphas of portfolios sorted by			
Decile	β^{Vac}	β^{Unemp}	β^{LFPR}	β^{IP}
Low	0.00	-0.19	-0.04	-0.08
2	0.13	-0.08	-0.02	0.05
3	0.11	0.01	0.02	0.06
4	0.01	0.00	0.01	0.09
5	0.01	0.10	0.03	0.06
6	0.00	0.09	0.03	0.04
7	0.07	0.03	0.03	0.01
8	0.02	0.08	0.07	-0.09
9	-0.07	0.13	0.08	-0.09
High	-0.22	-0.01	0.06	-0.13
Low-High	0.22	-0.18	-0.10	0.05
t-statistic	[1.63]	[-1.17]	[-0.74]	[0.34]

Table IA.VI
Fama-MacBeth Regressions of Monthly Stock Returns

This table reports the results of monthly Fama-MacBeth regressions. Monthly stock returns, in percent, 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 1954 to 2014.

Reg	β^{M}	β^{LFPR}	β^{Unemp}	β^{Vac}	β^{IP}	Controls
(1)	-0.045	0.005				No
	[-0.39]	[0.95]				
(2)	-0.050		0.046			No
	[-0.44]		[0.92]			
(3)	-0.036			-0.016		No
	[-0.31]			[-0.36]		
(4)	-0.040				-0.004	No
	[-0.34]				[-0.32]	
(5)	-0.043	0.004	0.097	0.043		No
	[-0.38]	[0.85]	[1.52]	[0.90]		
(6)	-0.037	0.006	0.079	0.054	-0.014	No
	[-0.34]	[1.14]	[0.96]	[1.06]	[-0.59]	
(7)	0.042	0.006				Yes
	[0.43]	[1.49]				
(8)	0.041		0.149			Yes
	[0.42]		[2.19]			
(9)	0.045			-0.163		Yes
	[0.46]			[-3.34]		
(10)	0.047				-0.029	Yes
	[0.48]				[-1.36]	
(11)	-0.043	0.004	0.097	0.043		Yes
	[-0.38]	[0.85]	[1.52]	[0.90]		
(12)	-0.037	0.006	0.079	0.054	-0.014	Yes
	[-0.34]	[1.14]	[0.96]	[1.06]	[-0.59]	

Table IA.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 2014.

	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	1.14	0.09	0.05	0.02	0.10	0.09	1.10	0.05	0.23	0.03
2	1.08	0.10	0.07	0.07	0.09	0.09	1.02	0.06	0.05	0.00
3	1.03	0.08	0.06	0.11	0.06	0.07	0.99	0.02	-0.04	-0.04
4	1.04	0.09	0.06	0.08	0.07	0.07	0.99	0.07	-0.06	-0.01
5	0.98	0.04	0.03	0.04	0.02	0.02	0.97	0.05	-0.10	-0.01
6	0.99	0.05	0.05	0.05	0.03	0.02	0.98	0.02	-0.12	0.00
7	0.97	0.02	0.01	0.01	0.01	0.01	0.99	0.03	-0.07	0.00
8	0.94	-0.02	-0.04	-0.05	-0.02	-0.02	1.01	0.05	-0.02	0.01
9	0.94	-0.07	-0.11	-0.07	-0.04	-0.04	1.06	0.06	0.06	-0.04
High	0.82	-0.22	-0.27	-0.26	-0.20	-0.19	1.07	0.06	0.29	-0.01
Low-High	0.33	0.31	0.32	0.28	0.30	0.29	0.04	-0.01	-0.06	0.04
t-statistic	[3.70]	[3.53]	[3.65]	[3.12]	[3.49]	[3.34]	[1.64]	[-0.20]	[-2.06]	[1.91]
B. Portfolios of Industries Sorted by Labor Market Tightness Loadings										
Low	1.28	0.32	0.19	0.11	0.26	0.25	1.01	0.25	0.25	0.09
2	1.17	0.20	0.09	0.13	0.15	0.14	1.04	0.16	0.15	0.00
3	1.13	0.18	0.07	0.03	0.13	0.11	1.02	0.21	0.17	0.01
4	1.10	0.15	0.06	0.07	0.12	0.11	0.99	0.16	0.19	0.02
5	1.08	0.13	0.06	0.08	0.10	0.09	1.00	0.13	0.18	0.00
6	1.08	0.12	0.03	0.06	0.09	0.08	1.02	0.14	0.19	-0.01
7	1.04	0.06	-0.03	0.00	0.03	0.02	1.04	0.16	0.21	-0.02
8	1.01	0.04	-0.06	0.02	0.01	0.01	1.04	0.21	0.23	-0.04
9	1.00	0.00	-0.10	-0.06	-0.05	-0.04	1.04	0.18	0.23	-0.08
High	0.88	-0.11	-0.25	-0.22	-0.15	-0.15	1.00	0.21	0.37	-0.10
Low-High	0.40	0.43	0.44	0.34	0.40	0.39	0.01	0.04	-0.12	0.19
t-statistic	[2.69]	[2.86]	[2.87]	[2.13]	[2.67]	[2.60]	[0.23]	[0.75]	[-2.17]	[3.98]

Table IA.VIII
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 2014 for all industries except Candy & Soda (1963 to 2014), Defense (1963 to 2014), Fabricated Products (1963 to 2014), Healthcare (1969 to 2014), and Precious Metals (1963 to 2014).

			Fraction of months in	
Industry	Average cond β^{θ}	Standard dev of β^{θ}	low β^{θ} quintile	high β^{θ} quintile
Tobacco Products	-0.090	0.207	0.391	0.137
Beer & Liquor	-0.060	0.153	0.321	0.081
Utilities	-0.046	0.109	0.296	0.086
Communication	-0.028	0.102	0.196	0.089
Precious Metals	-0.027	0.618	0.451	0.341
Banking	-0.026	0.147	0.334	0.112
Electronic Equipment	-0.026	0.144	0.227	0.099
Business Services	-0.022	0.117	0.213	0.092
Food Products	-0.022	0.119	0.197	0.079
Medical Equipment	-0.021	0.150	0.213	0.115
Candy & Soda	-0.019	0.185	0.316	0.199
Almost Nothing	-0.018	0.197	0.246	0.155
Shipping Containers	-0.017	0.120	0.198	0.089
Computers	-0.011	0.183	0.312	0.218
Insurance	-0.001	0.129	0.198	0.172
Entertainment	-0.001	0.175	0.279	0.193
Retail	-0.001	0.107	0.143	0.085
Chemicals	-0.001	0.085	0.067	0.103
Coal	0.000	0.269	0.312	0.350
Printing and Publishing	0.000	0.144	0.225	0.162
Pharmaceutical Products	0.003	0.125	0.126	0.168
Restaraunts, Hotels, Motels	0.003	0.135	0.152	0.184
Transportation	0.004	0.121	0.148	0.186
Consumer Goods	0.005	0.103	0.098	0.099
Petroleum and Natural Gas	0.007	0.127	0.169	0.180
Construction	0.008	0.171	0.218	0.217
Steel Works Etc	0.011	0.159	0.213	0.222
Agriculture	0.015	0.203	0.255	0.227
Defense	0.016	0.208	0.204	0.158
Electrical Equipment	0.017	0.093	0.077	0.118
Aircraft	0.018	0.133	0.182	0.193
Personal Services	0.018	0.175	0.174	0.192
Trading	0.020	0.119	0.095	0.178
Construction Materials	0.023	0.110	0.046	0.096
Business Supplies	0.027	0.126	0.143	0.185
Machinery	0.033	0.103	0.021	0.169
Apparel	0.035	0.155	0.122	0.260
Measuring and Control Equipment	0.036	0.120	0.078	0.201
Rubber and Plastic Products	0.036	0.124	0.099	0.231
Healthcare	0.040	0.261	0.275	0.310
Recreation	0.040	0.230	0.153	0.301
Fabricated Products	0.043	0.241	0.232	0.364
Wholesale	0.045	0.110	0.028	0.155
Shipbuilding, Railroad Equipment	0.046	0.207	0.172	0.301
Automobiles and Trucks	0.047	0.119	0.114	0.276
Textiles	0.062	0.135	0.069	0.293
Non-Metallic and Industrial Metal Mining	0.067	0.209	0.177	0.350
Real Estate	0.074	0.187	0.149	0.333

Table IA.IX
Summary Statistics

This table reports summary statistics for the matching efficiency shock (Δp) estimated as described in section G of this Internet Appendix, 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), and changes in industrial production (IP) calculated for the 1954 to 2014 period. Means and standard deviations are in percent.

			Correlations				
	Mean	StDev	Δp	ϑ	VAC	UNEMP	LFPR
Δp	0.04	15.65					
ϑ	0.11	5.43	0.42				
VAC	0.20	3.27	0.10	0.82			
UNEMP	0.08	3.30	-0.68	-0.83	-0.36		
LFPR	0.01	0.29	-0.12	-0.13	0.04	0.16	
IP	0.24	0.88	0.14	0.54	0.44	-0.47	0.04