Labor Search Frictions in Swedish Cross-Sectional Asset Pricing

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Abstract

This paper examines labor search frictions and cross-sectional equity returns in Sweden. We proxy for time-varying matching efficiency using the labor market tightness factor and shocks estimated from aggregate matching functions. Different from previous literature, we find no significant relation between firms' loading on labor search frictions and future equity returns. In explanation of these results, we show that Swedish firms do not behave systematically different on hiring policies across loadings, and that the labor market tightness factor does not capture matching efficiency shocks in Sweden. We argue that Swedish firms face high job separation costs which mitigates the propagation of shocks to matching efficiency. This study does not act as critique of previous literature but rather it provides insight into how differing labor market characteristics affect the implications of search frictions for asset prices.

Keywords: cross-sectional asset pricing, labor search frictions, matching efficiency, Swedish equity market

JEL Classification Codes: E24, G12, J21

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1 Introduction

Production-based asset pricing builds on the simple idea that the rate at which firms transform inputs of capital and labor into consumption goods should be closely tied to expected returns of financial assets. In this context, real, time-varying, macroeconomic risks affect firms' investment decisions, implying that the covariance between an asset's return and macroeconomic variables determines the asset's expected return (Cochrane, 1991). While much of the production-based asset pricing literature focuses on firms' investments in physical capital, academics' interest in firms' labor decisions has progressed in recent years.

A firm's investment rate, or marginal rate of transformation, does not only depend on the productivity of capital and labor but on the accessibility of those inputs. In accordance with matching theory, as pioneered by Diamond (1982), Mortensen (1982), and Pissarides (1985), firms look for workers with the required skills by posting vacancies. The likelihood of finding the best-fit candidate is affected by search frictions in the labor market. Building on this notion, Kuehn et al. (2017) show that labor search frictions are important determinants of cross-sectional stock returns in the U.S. Using data on stock returns over the period 1951 to 2014, they show that firms' loadings on changes in labor market tightness is robustly and inversely related to future returns. A risk-based explanation is presented; firms with high loading are less risky than firms with low loading, drawing on those firms having pro-cyclical valuations and hiring policies with respect to search frictions that consequently render them hedged against adverse matching efficiency shocks.

Following Kuehn et al. (2017), this paper studies the impact of labor search frictions on the Swedish equity market. Our contribution is two-fold. Firstly, to the best of our knowledge, there exists no out-of-country study on search frictions and the cross-section of stock returns. Secondly, since Sweden and the U.S. are two opposing extremes in terms of labor market characteristics (e.g. job security and labor union density), this study sheds light on how differing labor market characteristics affect the implications of search frictions for asset prices.

To study search frictions, which are unobservable, we construct the labor market tightness factor as proposed by Kuehn et al. (2017). We estimate firms' time-varying loadings on said factor and sort stocks into decile portfolios on the basis of their loading.

A portfolio, in which firms with low loading are bought and firms with high loading are sold, does not generate a significant Carhart (1997) four-factor alpha (*t*-statistic 1.00). Running Fama-MacBeth (1973) regressions of monthly stock returns yields an insignificant price of risk for the labor market tightness factor (*t*-statistic –0.54). We alternatively estimate shocks to matching efficiency using aggregate matching functions, and subsequently measure firms' loading on said shocks. The low-high matching efficiency shock portfolio generates a significant four-factor alpha of 0.95% (*t*-statistic 2.00). However, running Fama-MacBeth regressions makes it evident that this is not related to systematic risk compensation from search frictions, as the price of risk is not significantly different from zero (*t*-statistic –1.35).

To explain the absence of risk compensation, we set out to assess to what extent firms' labor decisions vary. To this end, we measure correlations between firms' labor-related characteristics and search frictions for firms sorted by their loading, and find that the cyclicality of labor decisions is fairly homogenous in the cross-section. Lastly, we examine the ability of the labor market tightness factor to capture matching efficiency shocks. We run a regression of labor market tightness on estimated matching efficiency shocks and industrial production, controlling for autocorrelation in labor market tightness. The coefficient for the shocks is insignificant (*t*-statistic –1.12), implying that the labor market tightness factor does not capture matching efficiency shocks in Sweden.

The remainder of this paper is organized as follows; Section 2 covers theory and related literature. Section 3 describes in detail the data used in this study. Section 4 presents the empirical approach and the results from the asset pricing tests on proxies for labor search friction. Section 5 discusses and interprets the empirical findings. Section 6 concludes the paper and gives directions for future research.

2 Theory & Related Literature

2.1 Asset Pricing Models

2.1.1 Fama-French Factors & Momentum

Why some stocks earn higher returns than others have for long been a topic of interest among academics. The Capital Asset Pricing Model (CAPM) (Sharpe, 1964; Lintner, 1965) is a cornerstone in the field of asset pricing and relates a stock's expected return to its exposure to the market factor (MKT), representing systematic market risk. Fama and French (1993) find that the size (SMB) and value (HML) factors, on top of the MKT factor, explain the cross-section of stock returns in the U.S. The SMB factor is constructed from the return of a long-short portfolio (small-big), in which small stocks are bought and big stocks are sold. In a similar fashion, the HML factor is defined as the return of a long-short portfolio (high-low) in which stocks with high book-to-market (value stocks) are bought and stocks with low book-to-market (growth stocks) are sold. Carhart (1997) proposes a fourth factor, momentum (MoM), which is constructed from a monthly rebalanced long-short portfolio (winners-losers), in which stocks with strong past performance are bought and stocks with weak past performance are sold.

2.1.2 Production-Based Asset Pricing & Labor

Many of the traditional asset pricing models explain an asset's return by its covariance with returns of other assets. Production-based asset pricing, which is built on the groundbreaking work by Cochrane (1991) and Jermann (1998), instead links real risks and business decisions to asset returns. Subsequent research adds to this notion by documenting the implications of firms' investment decisions for the cross-section of equity returns (e.g. Berk et al., 1999; Zhang, 2005).

Recently, related research has progressed to consider firms' labor characteristics; Donangelo (2014) find that labor mobility significantly relates to stock returns; Favilukis and Lin (2016) discover that rigid wages act like operating leverage for firms and consequently have consequences for asset pricing; Donangelo (2017) documents that labor leverage explains a substantial portion of the value premium; and Donangelo et al. (2019) provide evidence that firms with high labor share are more sensitive to economic shocks and thus have higher expected returns.

2.2 Matching Theory

Matching theory is an influential field in labor economics, explaining the aggregate macroeconomic outcomes of the interaction of individual searchers in the economy. A politically and academically important area of application is the process of job creation and separation. The outcome of this process is commonly illustrated with the Beveridge curve (Dow and Dicks-Mireaux, 1958), which graphically describes the relation between vacancies and unemployment. Movements up and down the curve reflect time-varying excess demand for labor. In times of high demand, the labor market is said to be "tight", meaning the vacancies-to-unemployed ratio (labor market tightness) is high, and consequently the probability of filling a vacancy is relatively low. Labor market tightness can moreover change via shifts of the Beveridge curve, which have been shown to be related to changes in matching efficiency, labor force growth, and labor market churning (Bleakley and Fuhrer, 1997).

While the Beveridge curve captures labor market dynamics, a more direct way of understanding the job matching process is to use aggregate matching functions (Petrongolo and Pissarides, 2001). In its simplest form, the matching function relates the number of jobs created to that of the number of unemployed looking for work and the number of vacant positions.

Commonly, the matching process is assumed to be random (Pissarides, 2000), so that unemployed job seekers and vacancies are randomly selected from the stock of unemployed and vacancies. Another well-established matching theory is stock-flow matching (Coles and Smith, 1998; Gregg and Petrongolo, 2005). Under this theory, newly unemployed workers first review the stock of vacancies. Those who do not match immediately will in subsequent periods only review and match toward the inflow of new vacancies, since the stock has already been sampled and there was no match. A vast amount of literature exists on different aggregate matching function specifications, see Petrongolo and Pissarides (2001) for an overview. We put forward the derivations of the two aforementioned aggregate matching functions in Appendix A.

2.3 The Labor Capital Asset Pricing Model

Contributing to the existing literature on production-based asset pricing, and the link between labor and asset prices, Kuehn et al. (2017) show that firms' exposure to labor search frictions explain the cross-section of stock returns in the U.S. By estimating firms' loadings on the change in labor market tightness, they find that firms with low loadings systematically outperform firms with high loadings. They assume that labor market tightness, θ_t, follows a log-linear law of motion

$$\log(\theta_t) = \tau_0 + \tau_\theta \log(\theta_{t-1}) + \tau_x \varepsilon_t^x + \tau_\rho \varepsilon_t^\rho, \tag{1}$$

where ε_t^x and ε_t^ρ are aggregate shocks to productivity and matching efficiency, respectively. The response of labor market tightness to efficiency shocks, τ_ρ, depends on two opposing factors; a cash flow effect and a discount effect. A positive shock to matching efficiency makes firms find new employees faster, and thus the marginal cost of hiring decreases. This increases excess demand of labor, so that firms post more vacancies ($\tau_\rho > 0$). However, if agents are not risk-neutral and if shocks to matching efficiency carry negative price of risk, a positive shock to matching efficiency increases discount rates, and consequently reduces the present value of hiring an additional worker. This effect reduces excess demand of labor and implies $\tau_\rho < 0$. Kuehn et al. (2017) find that the cash flow effect is dominant ($\tau_\rho > 0$), so that firms' loadings on labor market tightness act as proxy for loadings on matching efficiency. As a result, firms with high loadings are hedged against adverse matching efficiency shocks, since those firms have pro-cyclical cash flows with respect to matching efficiency, and hence hire more in times of low marginal hiring costs. Conversely, firms with low loadings have counter-cyclical cash flows and hiring policies with respect to matching efficiency. Lowly loaded firms are hence more risky, and have higher expected returns.

The aggregate shocks to productivity and matching efficiency are mapped onto the market return and labor market tightness, respectively. This implies that expected excess returns obey a two-factor model

$$\mathbb{E}_t\left[R_{i,t+1}^e\right] = \beta_{i,t}^M \lambda_t^M + \beta_{i,t}^\theta \lambda_t^\theta, \tag{2}$$

where $\beta_{i,t}^M$ and $\beta_{i,t}^\theta$ are factor loadings, and λ_t^M and λ_t^θ are factor risk premia of the MKT factor and the labor market tightness factor, respectively.

3 Data

Our sample includes data on monthly stock returns, book equity, and market equity, on Swedish common stocks listed on the Swedish Stock Exchange (SSE) and associated Multi-Lateral Platforms (MLP) and Over-the-Counter (OTC) markets spanning over the period January 1983 to December 2016. The depth and reliability of the Finbas database, provided by the Swedish House of Finance (SHoF), ultimately encourage us to use it as the sole provider of aforementioned stock data. It is moreover free from survivorship bias. Again making use of SHoF, we acquire value-weighted monthly Swedish Carhart (1997) four-factor time-series ranging between February 1983 and December 2016. We complement the dataset with time-series on yearly firm fundamentals from Thomson Datastream; total assets (WC02999), capital expenditures (WC04601), salaries and benefits expenses (WC01084), total debt (WC03255), employees (WC07011), net income (WC01751), and net sales (WC01001).

The resulting unfiltered dataset comprises 102,774 monthly observations from 725 unique stocks. We subsequently filter the dataset, firstly by matching the time period of our stock data with that of the risk factor data, and secondly by dropping observations with non-valid returns or market equity. We also require each stock to have more than 36 observations, and each stock must have a minimum of 24 valid returns in every period of 36 months. If a firm has dual class shares, we only keep the stock that is deemed the main share on the basis of past liquidity. The described filtering procedure yields our final dataset, which consists of 67,656 monthly observations from 404 unique stocks.

We collect, using the OECD database, Swedish monthly time-series data on industrial production, the 3-month T-bill, and the 10-year T-note. The 1-month T-bill rate is gathered from SHoF, while the consumer price index stems from SCB. All data range between the period February 1983 to December 2016, except for the 3-month and 10-year rates which span over December 1986 to December 2016 due to data limitations.

Essentially, stock return data in conjunction with labor statistics are the backbone of this paper. Hence, we collect data on monthly labor statistics through the Swedish Public Employment Service (SPES) and Statistics Sweden (SCB). The labor market tightness factor, constructed in Section 4.1.1, only depends on vacancy- and unemployment levels, which are gathered from SPES and SCB respectively for the period February 1983 to December 2016.

The matching functions, used in Section 4.2.1, require additional data. First and foremost, they make use of the number of people that match – proxied by hires identified by SPES as the number of people in a month that change status from “openly unemployed” or “program participants” to a status classified as employment. Unemployed job seekers are characterized as people who identify as any of the two aforementioned statuses. Note that we differ on the definition and measurement of unemployed between labor market tightness and the matching functions. For the labor market tightness, statistics on unemployment from SCB is used as it spans over a longer time period. For the matching functions, however, statistics on unemployment from SPES is used to prohibit estimation bias which would otherwise occur since matches are based on the SPES unemployment definition The stock-flow matching function, moreover, separates vacancy- and unemployment levels into two fragments; inflows and stocks. As there exists no such fragmentation in the SPES unemployment data, we backtrack inflows as the change in two consecutive unemployment stock levels adjusted for the number of hires corresponding to that month. The resulting dataset comprises stocks and inflows of unemployment and vacancies, as well as matches for the period January 1992 to December 2016, which is depicted in Appendix C.

Backtracking unemployment inflows has its limitations, as it could be that people withdraw or deregister from SPES in spite of not actually becoming employed, consequently yielding under-estimated unemployment inflows. Moreover, far from all job vacancies are reported to SPES. Therefore, while the SPES labor statistics is generally accepted as being well-representative of the Swedish labor market, one has to acknowledge that it does not capture the true and complete labor statistics in Sweden. Lastly, our definition of job seekers neglects employed job seekers, in turn potentially causing bias to our point estimates of the matching functions. In particular, an employed job seeker is likely to be more responsive to changes to labor market tightness. Thus, the elasticities of vacancies and unemployed job seekers with regards to the number of matches could be under- and overestimated, respectively (Forslund and Johansson, 2007).

4 Empirical Approach & Results

In this section, using portfolio sorts and Fama-MacBeth (1973) regressions, we are unable to document a significant relation between stock return loadings on labor market tightness and future returns. We find similar evidence upon substituting the labor market tightness factor for estimated matching efficiency shocks, giving rise to an analysis of firm labor decision cyclicality and the law of motion for labor market tightness.

4.1 Labor Market Tightness

4.1.1 The Labor Market Tightness Factor

We define labor market tightness as the ratio of aggregate vacant postings to unemployed workers at time *t*, or, equivalently in rates relative to the number of people in the labor force. We garner data on unemployment and labor force through SCB and complement it with vacancy statistics from SPES. Equation 3 depicts the ratio

$$\theta_t = \frac{Vacancies_t}{Unemployed_t} = \frac{Vacancy\ rate_t}{Unemployment\ rate_t}. \tag{3}$$

We identify that Swedish labor statistics are highly affected by seasonal effects. Consequently, to reasonably interpret the labor dynamics over time, we adjust for seasonality using the U.S. Census Bureau X-11ARIMA model.[1]

Figure 1 depicts the monthly time series of LMT and its components, from which one can identify that labor market tightness acts fairly pro-cyclical over the full sample period. This is a direct consequence of the pro-cyclicality of vacancies – its numerator – and the counter-cyclicality of unemployment – its denominator. Corresponding cyclical behavior of aforementioned objects have been documented on the U.S. labor market by Shimer (2005).

[1] We refrain from using X-13ARIMA-SEATS to avoid over-adjusting labor statistics with regards to outliers.

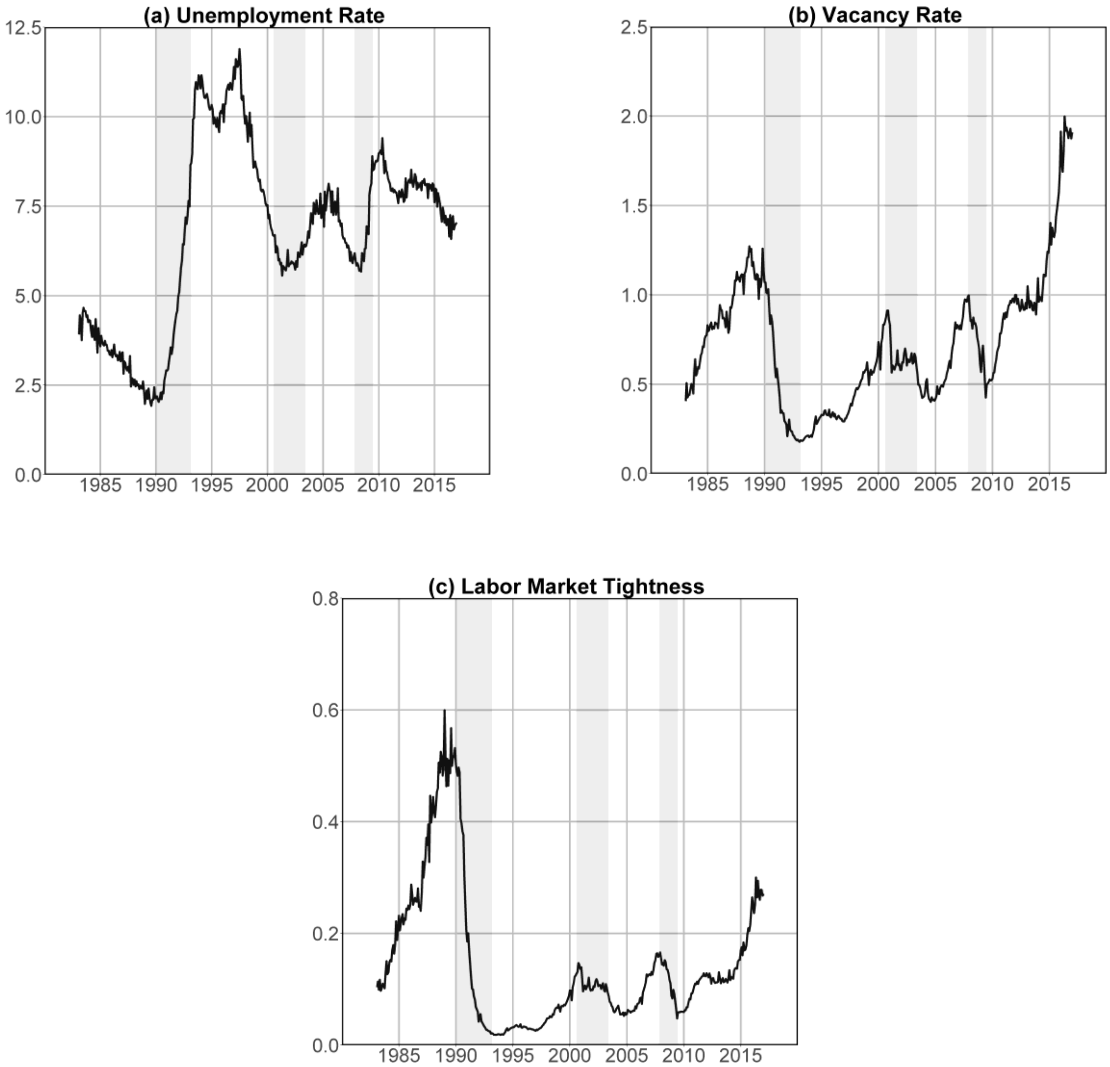

Figure 1: Labor Market Tightness and its Components. This figure depicts seasonally adjusted time-series of labor market tightness (c) and its underlying components, unemployment (a) and vacancies (b), both of which are in rates relative to the number of people in the labor force. The underlying components, (a) and (b), are expressed in percent. The data is monthly. The time-series span over the period January 1983 to December 2016. The grayed areas are mapped OECD recession indicators for Sweden; February 1990 to February 1993, August 2000 to May 2003, and November 2007 to June 2009.

Following Kuehn et al. (2017), we define the labor market tightness factor as the log change of two consecutive vacancy-unemployment ratios. Said factor essentially serves to capture time-varying aggregate matching efficiency, and is the key variable underpinning our analysis in this section where we seek to examine its implications for cross-sectional equity returns. The factor is described in Equation 4

$$\vartheta_t = \log(\theta_t) - \log(\theta_{t-1}), \tag{4}$$

and Table I provides summary statistics for the factor and its underlying components together with selected macro variables.

Table I: Summary Statistics

This table depicts summary statistics for the labor market tightness factor (ϑ), changes in the vacancy rate (VAC), changes in the unemployment rate (UNEMP), changes in industrial production (IP), changes in the consumer price index (CPI), 1-month T-bill rate (TB), and term spread (TS). The considered time period is February 1983 to December 2016 for all variables except TS which spans over December 1986 to December 2016. The data is monthly. Means and standard deviations are in percent.

			Correlations					
	Mean	StdDev	ϑ	VAC	UNEMP	IP	CPI	TB
ϑ	0.24	8.88						
VAC	0.62	6.87	0.80					
UNEMP	0.29	5.33	–0.63	–0.04				
IP	0.16	1.99	0.09	0.14	0.03			
CPI	0.23	0.51	–0.04	–0.03	0.04	0.06		
TB	0.48	0.39	–0.13	–0.10	0.09	0.01	0.36	
TS	1.09	1.34	0.24	0.19	–0.15	0.10	–0.18	–0.53

Following the previous findings we made on the behavior of the components underlying the labor market tightness ratio, it comes as no surprise that the labor market tightness factor is strongly positively (negatively) correlated with vacancies (unemployment). Moreover, we find that the labor market tightness factor is weakly correlated to a selection of the macro variables used by Kuehn et al. (2017); industrial production (IP), consumer price index (CPI), 1-month T-bill rate (TB) and term spread (TS)[2]. Given the weak relation between labor market tightness to that of the macro variables, it appears to be of low risk that changes in labor market tightness is driven by these variables.

We note that changes in vacancy rates are characterized by higher standard deviation relative to changes in unemployment rates (6.87% and 5.33%, respectively). Correspondingly for the U.S., Kuehn et al. (2017) find that changes in said components

[2] TS is defined as the spread between the Swedish 3-month T-bill and the Swedish 10-year T-note rates.

amount to approximately 3.30%, respectively. The means of said components in Sweden are higher than what the comparable research paper find in the U.S. (0.62% and 0.29% for Sweden while 0.20% and 0.08% for the U.S. for vacancy and unemployment, respectively). Ultimately, we note that the labor market tightness factor in Sweden is characterized by a higher mean and standard deviation (0.24% and 8.88%, respectively) as compared to the U.S. (0.11% and 5.43%, respectively). One should note, however, that the considered time horizon in the U.S. paper is different from that of our study on Sweden (1954 to 2014 and 1983 to 2016, respectively).

4.1.2 Cross-Sectional Asset Pricing Tests

To empirically study the explanatory power of aggregate matching efficiency on the cross-section of stock returns, we estimate loadings for each individual stock using a two-factor model constituted by the market excess return, R_τ^M, and the labor market tightness factor, ϑ_τ. To allow for time variation in estimated loadings, we run 36-month[3] rolling regressions for each stock $i = 1,2 \dots N$

$$R_{i,\tau}^e = \alpha_{i,t} + \beta_{i,t}^M R_\tau^M + \beta_{i,t}^\theta \vartheta_\tau + \varepsilon_{i,\tau}, \qquad \tau \in \{t-35, t\}, \tag{5}$$

where $R_{i,\tau}^e$ is the monthly stock excess return in month τ, $\alpha_{i,t}$ is the intercept, and R_τ^M and ϑ_τ with associated $\beta_{i,t}^M$ and $\beta_{i,t}^\theta$ are the market excess return and labor market tightness factor respectively with related estimated loadings. To insure the validity of obtained loadings, we require each stock to have a minimum of 24 valid returns in every period of 36 months upon estimation.

Having employed said regressions, we seek to rank all stocks into deciles by their loadings on the labor market tightness factor (β^θ). We identify that monthly Swedish labor statistics are published mid-month and consequently skip a month to allow for the information to become publicly available. Firms are hence assigned into deciles at the end of June of year *t* on the basis of their loading end of May of year *t*. The resulting 10 portfolios are held without rebalancing from beginning of July of year *t* to end of June of year *t+1*, and are then reformed at the end of June of year *t+1*.

[3] Our results are not fundamentally different upon using 24, 48, or 60 months to estimate loadings.

Table II: Characteristics of Labor Market Tightness Factor Decile Portfolios

This table contains mean characteristics for portfolios of stocks sorted by their loadings on labor market tightness (β^{θ}). β^{M} is the market beta, BM the book-to-market ratio, and ME the market equity decile. RU is the 12-month run-up return, AG the asset growth rate, IK the investment rate, HN the hiring rate, and LEV the leverage, all in percent. Portfolios are formed in June of year *t* on the basis of their loading as of May of year *t*, and held without rebalancing from July of year *t* to June of year *t+1* before being reformed. Mean characteristics are calculated annually and then averaged over time. The period is July 1986 to December 2016.

Decile	β^{θ}	β^{M}	BM	ME	RU	AG	IK	HN	LEV
Low	–0.36	1.08	0.79	5.05	23.44	8.97	5.21	–0.10	18.02
2	–0.21	1.09	0.80	5.43	17.81	11.55	4.52	3.74	23.21
3	–0.14	0.95	0.72	5.67	21.59	11.34	4.47	2.41	22.55
4	–0.08	0.94	0.72	5.88	19.06	18.58	5.98	3.15	22.39
5	–0.03	1.01	0.79	5.89	17.77	17.08	6.73	2.62	21.75
6	0.01	1.02	0.81	6.09	20.45	11.02	6.30	6.15	23.30
7	0.05	0.97	0.70	6.00	21.05	12.36	6.10	3.49	22.61
8	0.11	0.98	0.74	5.68	18.66	14.23	5.15	5.28	19.44
9	0.19	1.07	0.76	5.18	17.91	10.52	5.68	5.33	21.29
High	0.37	1.00	0.81	3.92	21.99	14.92	6.43	1.50	17.52

Reviewing Table II, which depicts the mean firm characteristics for the resulting decile portfolios across the period July 1986 to December 2016, we find that the average loading on the labor market tightness factor ranges between –0.36 and 0.37. This dispersion is smaller than what is empirically observed in the U.S. (Kuehn et al., 2017), ranging between –0.80 to 0.92. We establish moreover that average loadings of all decile portfolios, both individually and adjacently, are statistically significant different from zero – signifying meaningful loading estimates.

Reviewing the average firm-specific characteristics for all decile portfolios, we identify that the lowest and highest decile portfolios are generally characterized by lower size (ME), stronger recent performance (RU), lower hiring rate (HN), and lower leverage (LEV) relative to the other decile portfolios. Essentially, we find no strong and conclusive pattern of firm-specific characteristics across loadings on the labor market tightness factor.

Table III: Performance of Labor Market Tightness Factor Decile Portfolios

This table reports average monthly raw returns and unconditional alphas, in percent, and four-factor loadings for the 10 portfolios of stocks sorted by their loading on the labor market tightness factor, as well as for the low-high β^{θ} portfolio. The value-weighted portfolios are formed in June of year *t* on the basis of their loading as of May of year *t*, and held without rebalancing from July of year *t* to June of year *t+1* before being reformed. The bottom row contains *t*-statistics for the low-high portfolio. The period is July 1986 to December 2016.

	Raw	Unconditional Alpha			FF4-Loadings			
Decile	Return	CAPM	FF3	FF4	MKT	SMB	HML	MoM
Low	1.28	0.18	0.16	0.17	0.95	0.07	0.14	–0.03
2	1.24	0.04	–0.05	–0.06	1.09	–0.05	0.16	0.01
3	1.27	0.17	0.15	0.16	0.97	0.07	0.14	–0.01
4	1.67	0.54	0.57	0.55	1.02	0.07	0.03	0.04
5	1.63	0.45	0.45	0.53	1.00	0.03	0.03	–0.20
6	1.34	0.16	0.04	0.10	1.01	–0.07	0.17	–0.13
7	1.14	0.09	0.07	0.06	0.90	–0.01	0.02	0.04
8	0.97	–0.11	–0.09	–0.09	0.94	0.07	0.05	0.01
9	1.24	0.14	0.01	0.02	0.94	–0.07	0.20	–0.01
High	0.88	–0.20	–0.14	–0.15	0.98	0.25	0.19	0.01
Low-high	0.39	0.38	0.30	0.32	–0.03	–0.18	–0.05	–0.04
t-statistic	[1.00]	[0.97]	[0.76]	[0.80]	[–0.47]	[–2.21]	[–0.66]	[–0.67]

As our dataset is comprised of many small stocks, we look to the value-weighted returns of the decile portfolios. Table III depicts monthly raw returns, alphas and betas for respective decile portfolio between July 1986 and December 2016, as well as for the portfolio that is long the lowest- and short the highest β^{θ} portfolios. We control our portfolio returns for well-established benchmarks; CAPM, Fama-French (1993) three-factor model, and Carhart (1997) four-factor model.

Firstly, we do not document a systematic negative relation between loadings on the labor market tightness factor and stock performance in Sweden. Instead, we find that returns across the decile portfolios fluctuate in an inconclusive pattern. This holds true for both raw- and risk-adjusted returns. The low-high portfolio yields an economically large though statistically insignificant (*t*-statistic 1.00) monthly excess return of 0.39%. Using the four-factor model, we still find that the low-high portfolio yields a sizeable but insignificant (*t*-statistic 0.80) monthly unconditional alpha of 0.32%. Moreover, we see that the portfolio loads negatively on the SMB risk factor (*t*-statistic –2.21). All things considered, these findings shed some doubt as to whether loading on the labor market tightness factor is systematically related to expected equity returns in Sweden.

Figure 2: Cumulative Log Return of Low-high Portfolio. This figure depicts the cumulative log return of the low-high portfolio loading on the labor market tightness factor. The data is monthly. The time period is July 1986 to December 2016. The grayed areas are mapped OECD recession indicators for Sweden; February 1990 to February 1993, August 2000 to May 2003, and November 2007 to June 2009.

Inspecting the cumulative low-high portfolio return over the period July 1986 to December 2016 in Figure 2, we find that it yields 39.77%. We observe that said portfolio performs strongly during the 1990-1993 crisis, signifying counter-cyclical returns. However, said counter-cyclical pattern weakens in the two subsequent crisis periods; 2000-2003 and 2007-2009.

Kuehn et al. (2017) find that the low-high portfolio return generally increases over time, and that it momentarily declines in periods of recession. This is then argued to indicate a persisting relation between loading on the labor market tightness factor and stock performance. Consequently, and while we acknowledge that the considered time horizon in our empirical study is shorter than that of the comparable paper, we find that the low-high portfolio return does not move in a similar pattern. This finding further shed doubt as to whether loading on the labor market tightness factor in fact is systematically related to expected equity returns in Sweden.

Our findings hitherto do not point toward an existent systematic relation between loading on labor market tightness and future equity performance in Sweden. Conducting such univariate analysis, however, is not optimal as it does not incorporate various firm-level characteristics which previously have been shown to relate to future returns. Moreover, it does not consider the covariance between the factors. Consequently, using a standard two-pass regression approach (Fama-MacBeth, 1973), we run step-wise monthly regressions of stock excess returns on lagged labor market tightness loadings, excess market loadings, and control variables for well-established determinants of the cross-section of stock returns; book-to-market (BM), market equity (ME), and run-up performance (RU). The timing of the control variables follow that of Fama and French (1992).[4] Following the empirical findings by Ang et al. (2018) on portfolios destroying information and causing larger standard errors, we disregard from conducting Fama-MacBeth regressions on portfolios and instead consider individual stocks. Having already estimated rolling market- and labor market tightness loadings in Equation 5, that is the first-stage, we run second-stage cross-sectional regressions in a pooling scheme over time $t = 1,2 \ldots T$ and across assets $i = 1,2 \ldots N$

$$R^e_{i,t+1} = a_{i,t} + \hat{\beta}^M_{i,t}\lambda^M + \hat{\beta}^\theta_{i,t-1}\lambda^\theta + V'_{i,t}\lambda', \tag{6}$$

whereas λ^M, λ^θ and λ^i are the average prices of risk for the market factor, labor market tightness factor, and the control variables vector (V'), respectively. $\alpha_{i,t}$ is the individual pricing error. The timing of $\hat{\beta}^\theta$ considers that labor statistics are published with a lag.

Considering our dataset is comprised of many small firms, we use two alternative data samples; the full sample dataset and a sub-sample in which micro-cap firms are excluded. We do so to distinguish if micro-cap stocks, which tend to have more extreme values and which account for a large part of the dataset though only a minor part of the total market capitalization, potentially have a distorting effect. We define micro-caps as stocks with market equity below the 20th dataset percentile.[5] Moreover, to cope with potential heteroscedasticity and autocorrelation in returns and innovations, we use Newey-West (1987) standard errors. The empirical findings are depicted in Table IV.

[4] See Appendix B for detailed information concerning the timing.
[5] Fama and French (2008) similarly define micro-cap firms as the 20th percentile of NYSE.

Table IV: Fama-MacBeth Regressions of Monthly Stock Returns

This table depicts the results of Fama-MacBeth (1973) regressions of monthly stock returns on lagged labor market tightness loadings (β^{θ}), market betas (β^{M}), log market equity (ME), log book-to-market (BM), and 12-month run-up returns (RU). The data is monthly. Average coefficients and Newey-West (1987) *t*-statistics are reported. The period is March 1986 to December 2016.

	Full Sample				Excluding Micro Cap			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
β^{θ}	–0.20	–0.18	–0.22	–0.24	–0.53	–0.60	–0.56	–0.30
t-statistic	[–0.54]	[–0.48]	[–0.61]	[–0.62]	[–1.28]	[–1.49]	[–1.43]	[–0.82]
β^{M}	–0.03	–0.10	–0.20	–0.20	0.00	–0.02	–0.12	–0.12
t-statistic	[–0.13]	[–0.41]	[–0.84]	[–0.86]	[0.01]	[–0.08]	[–0.46]	[–0.50]
BM		0.18	0.17	0.33		0.00	0.01	0.17
t-statistic		[1.18]	[1.04]	[2.29]		[0.01]	[0.08]	[1.46]
ME			0.00	–0.04			0.03	0.01
t-statistic			[–0.07]	[–0.60]			[0.45]	[0.08]
RU				1.13				1.12
t-statistic				[2.99]				[2.91]

Regression (1) on the full sample provides no evidence of a statistically significant negative price of risk for the labor market tightness factor (*t*-statistic –0.54). This empirical evidence sustains upon controlling for the control variables in regressions (2-4). Upon excluding micro-cap firms, we similarly find that the negative price of risk for the labor market tightness factor is insignificant, in particular upon controlling for run-up performance (RU). All things considered, our empirical findings on Sweden suggest that there exist no statistically significant relation between loadings on the labor market tightness factor and future equity returns.

4.2 Matching Efficiency Shocks

4.2.1 Estimating Shocks

There exists several methods to capture time-varying aggregate matching efficiency. In addition to the labor market tightness factor, Kuehn et al. (2017) estimate shocks to matching efficiency as the residuals from an empirically fitted Beveridge curve. This approach is common but not free from limitations, seeing as it has been documented that shifts in the Beveridge curve could stem from forces other than the matching process; e.g. significant drops in labor force growth and the degree of labor market churning (Bleakley and Fuhrer, 1997). In light of these issues, and given the availability of detailed labor data in Sweden, we use aggregate matching functions in an effort to better isolate the job matching process. More specifically, we estimate two common matching functions using monthly time-series from SPES on stocks and inflows of unemployment and vacancies, as well as data on matches. Due to data limitations, the considered time period is 1992-2016.[6, 7]

Firstly, we estimate a random matching function, in which matches during a period (M_t) depend on the beginning-of-period stocks of unemployed job seekers (U_{t-1}) and vacancies (V_{t-1}). Beginning-of-period stocks are used to mitigate time aggregation problems potentially causing simultaneity bias (Coles and Smith, 1998). The random matching function can then be described as a Cobb-Douglas function of the form

$$M_t = f_t(U_{t-1}, V_{t-1}) = A_t U_{t-1}^{\alpha_1} V_{t-1}^{\beta_1}, \tag{7}$$

where α_1 and β_1 are matching elasticities. A_t is a mismatch parameter measuring time-varying matching efficiency, and is defined as

$$A_t = A e^{\gamma_t + \varepsilon_t}, \tag{8}$$

where time effects are captured by γ_t and ε_t is the unexplained part of the variation in matches. By inserting Equation 8 into Equation 7 and taking logs, we obtain

$$m_t = \alpha + \alpha_1 u_{t-1} + \beta_1 v_{t-1} + \gamma_t + \varepsilon_t. \tag{9}$$

---

[6] Unemployment inflow for September 1994 is non-positive, and consequently omitted due to not being economically meaningful.
[7] See Appendix C for labor statistics time-series.

Additionally, we consider a stock-flow matching function. Under stock-flow matching, matches depend not only on the beginning-of-period stocks of unemployed job seekers and vacancies but on the inflows of unemployed ($\acute{U}_t$) and vacancies ($\acute{V}_t$)

$$M_t = f_t(U_{t-1}, V_{t-1}, \acute{U}_t, \acute{V}_t) = A_t U_{t-1}^{\alpha_1} V_{t-1}^{\beta_1} \acute{U}_t^{\alpha_2} \acute{V}_t^{\beta_2}. \tag{10}$$

By inserting Equation 8 into Equation 10 and taking logs, we obtain

$$m_t = \alpha + \alpha_1 u_{t-1} + \beta_1 v_{t-1} + \alpha_2 \acute{u}_t + \beta_2 \acute{v}_t + \gamma_t + \varepsilon_t. \tag{11}$$

Both the random- and the stock-flow matching functions, Equation 9 and 11, can then be estimated using fixed effects models. In both models, time effects in the form of annual and seasonal fixed effects are included – in line with specifications used in previous studies (e.g. Coles and Smith, 1998). The results are shown in Table V.

Table V: Fitting the Matching Efficiency Functions

The table reports the results of regressions of number of matches on beginning-of-period stocks of vacancies (v_{t-1}) and unemployed (u_{t-1}), as well as on inflows of vacancies ($\acute{v}_t$) and unemployed ($\acute{u}_t$). All variables are in log. The data is monthly. Annual- and seasonal fixed effects are included. Average coefficients, Newey-West (1987) *t*-statistics, and adjusted R^2 are reported. The period is February 1992 to December 2016.

	Random Matching	Stock-Flow Matching
v_{t-1}	0.21	0.06
t-statistic	[4.78]	[1.55]
u_{t-1}	0.91	0.97
t-statistic	[10.30]	[11.27]
$\acute{v}_t$		0.32
t-statistic		[8.04]
$\acute{u}_t$		0.04
t-statistic		[1.81]
Adj. R^2	0.15	0.30

We initially observe that the point estimates of the fitted random matching function suggest that stocks of unemployment and vacancies both have a significant effect on the number of matches. However, in the stock-flow specification, the point estimate of the vacancy stock drastically decreases and becomes insignificant. This, coupled with the fact that adjusted R^2 doubles when the flow-variables are added, suggest that stock-flow matching reflect the Swedish labor matching process better than random matching. Similar results have been documented in a previous study investigating aggregate matching functions in Sweden (Forslund and Johansson, 2007). Drawing on these findings, we use the stock-flow function to estimate matching efficiency shocks. Considering, however, potential biases that have been documented to favor stock-flow matching, e.g. simultaneity bias (Coles and Petrongolo, 2008), in

Appendix D we investigate whether our empirical results fundamentally differ if we instead use shocks estimated from the random matching function.

The residuals of the fitted stock-flow matching function, ε, represent the part of the actual matching rate that cannot be explained by our matching function, and thus can be interpreted as shocks to aggregate matching efficiency. Since our objective is to isolate the unexpected part of labor search frictions, we test for auto-correlation in the residuals using the Bayesian information criteria (BIC). We find evidence that the stock-flow residuals follow an AR(1) process

$$\varepsilon_t = \beta\varepsilon_{t-1} + \rho_t. \tag{12}$$

We subsequently define ρ as shocks to matching efficiency, and plot its monthly time-series in Figure 3.

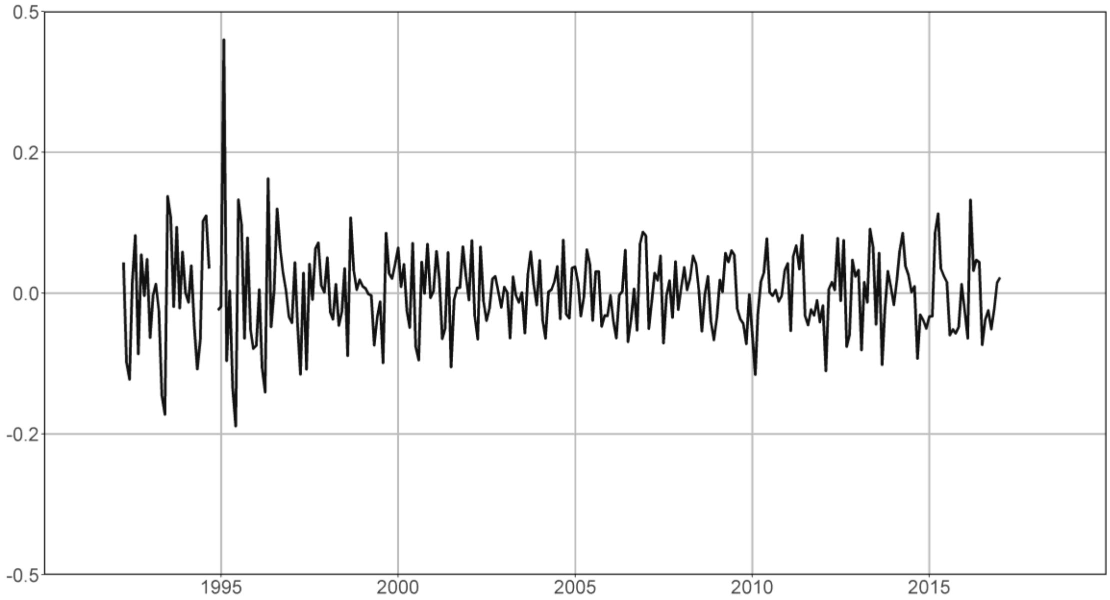

Figure 3: Estimated Matching Efficiency Shocks. This figure depicts the time-series of matching efficiency shocks, ρ, estimated from the stock-flow matching function. The data is monthly. The time period is March 1992 to December 2016.

4.2.2 Cross-Sectional Asset Pricing Tests

Our intention is to again test the asset pricing implications of labor search frictions, now making use of the estimated matching efficiency shocks, ρ, constructed in the previous section. To this end, we follow the approach stated in Section 4.1.2 but instead estimate 36-month[8] rolling loadings by regressing stock excess returns against market excess returns and estimated matching efficiency shocks. We then allocate stocks into decile portfolios on the basis of their estimated matching efficiency shock loadings, β^{ρ}.

Table VI: Characteristics of Matching Efficiency Shock Decile Portfolios

This table contains mean characteristics for portfolios of stocks sorted by their loadings on estimated matching efficiency shocks (β^{ρ}). β^{M} is the market beta, BM the book-to-market ratio, and ME the market equity decile. RU is the 12-month run-up return, AG the asset growth rate, IK the investment rate, HN the hiring rate, and LEV is the leverage, all in percent. Portfolios are formed in June of year *t* on the basis of their loading as of May of year *t*, and held without rebalancing from July of year *t* to June of year *t+1* before being reformed. Matching efficiency shocks are estimated from the stock-flow matching function. Mean characteristics are calculated annually and then averaged over time. The period is July 1995 to December 2016.

Decile	β^{ρ}	β^{M}	BM	ME	RU	AG	IK	HN	LEV
Low	–0.49	0.97	0.74	4.16	24.38	13.88	5.55	3.40	19.44
2	–0.23	0.98	0.84	5.36	15.21	28.25	4.90	9.07	20.46
3	–0.14	1.03	0.70	5.90	19.19	12.83	4.95	6.21	19.27
4	–0.07	0.94	0.76	5.88	20.48	9.91	4.55	0.97	18.91
5	–0.02	0.91	0.73	6.11	18.38	6.77	4.08	2.22	18.32
6	0.04	1.16	0.74	6.07	19.53	12.90	5.26	2.53	22.41
7	0.09	0.96	0.73	5.92	19.58	8.98	4.29	2.44	19.09
8	0.16	1.07	0.73	5.71	16.45	9.96	4.69	3.07	20.30
9	0.24	1.07	0.68	5.31	19.55	18.28	5.09	4.09	16.43
High	0.46	1.20	0.71	4.41	19.74	12.85	5.82	3.65	18.59

In Table VI, we present key characteristics of decile portfolios which independently load on estimated matching efficiency shocks. The loading dispersion spans from –0.49 to 0.46, which is somewhat larger than what we observed upon loading on the labor market tightness factor in Table II. Average loadings of all decile portfolios, both individually and adjacently, are statistically significant different from zero. The low- and high decile portfolios are generally comprised of smaller firms. We also note that aforementioned portfolios generally have somewhat higher investment rate (IK) in comparison to the other portfolios, and that the low portfolio generally comprises firms with stronger run-up performance (RU). Ultimately, we are unable to establish any systematic pattern in firm characteristics across the decile portfolios.

[8] Our results are not fundamentally different upon using 24, 48, or 60 months to estimate loadings.

Table VII: Performance of Matching Efficiency Shock Decile Portfolios

This table reports average monthly raw returns and unconditional alphas, in percent, and four-factor loadings for the 10 portfolios of stocks sorted by their loading on estimated matching efficiency shocks, as well as for the low-high β^{ρ} portfolio. The value-weighted portfolios are formed in June of year *t* on the basis of their loading as of May of year *t*, and held without rebalancing from July of year *t* to June of year *t+1* before being reformed. Matching efficiency shocks are estimated from the stock-flow matching function. The bottom row contains *t*-statistics for the low-high portfolio. The period is July 1995 to December 2016.

	Raw	Unconditional Alpha			FF4-Loadings			
Decile	Return	CAPM	FF3	FF4	MKT	SMB	HML	MoM
Low	1.77	0.78	0.78	0.78	1.00	0.32	0.19	0.00
2	1.69	0.63	0.59	0.72	0.89	–0.09	0.03	–0.21
3	1.06	0.07	–0.08	–0.05	0.97	0.04	0.30	–0.05
4	1.37	0.37	0.22	0.27	0.94	–0.06	0.23	–0.07
5	1.24	0.31	0.25	0.24	0.86	–0.01	0.10	0.01
6	0.84	–0.21	–0.33	–0.33	1.05	0.04	0.23	0.00
7	1.19	0.33	0.29	0.23	0.86	0.17	0.16	0.11
8	0.71	–0.57	–0.47	–0.48	1.21	0.05	–0.15	0.02
9	0.75	–0.36	–0.33	–0.32	1.02	–0.02	–0.06	–0.02
High	0.86	–0.31	–0.27	–0.18	1.09	0.18	0.05	–0.16
Low-high	0.90	1.09	1.05	0.95	–0.09	0.14	0.14	0.17
t-statistic	[1.89]	[2.28]	[2.20]	[2.00]	[–0.94]	[1.34]	[1.38]	[2.37]

We collect time-series of monthly, value-weighted portfolio returns over the period July 1995 to December 2016. Returns, unconditional alphas, and factor loadings for the decile portfolios and the low-high β^{ρ} portfolio are depicted in Table VII. There is no consistent pattern in raw- and risk-adjusted returns across loadings. We find weak evidence (*t*-statistic 1.89) of the low-high portfolio yielding a monthly excess return different from zero. The monthly unconditional four-factor alpha of the low-high portfolio is statistically different from zero (*t*-statistic 2.00) and is economically sizeable at 0.95%. The low-high portfolio loads significantly on the MoM factor (*t*-statistic 2.37).

Table VIII: Fama-MacBeth Regressions of Monthly Stock Returns

This table depicts the results of Fama-MacBeth (1973) regressions of monthly stock returns on lagged estimated matching efficiency shock loadings (β^{ρ}), market betas (β^{M}), log market equity (ME), log book-to-market (BM), and 12-month run-up returns (RU). Matching efficiency shocks are estimated from the stock-flow matching function. The data is monthly. Average coefficients and Newey-West (1987) *t*-statistics are reported. The period is June 1995 to December 2016.

	Full Sample				Excluding Micro Cap			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
β^{ρ}	–0.55	–0.34	–0.36	–0.38	–0.35	–0.28	–0.25	–0.26
t-statistic	[–1.35]	[–0.81]	[–0.89]	[–0.96]	[–0.87]	[–0.72]	[–0.66]	[–0.70]
β^{M}	–0.30	–0.34	–0.33	–0.25	–0.30	–0.33	–0.34	–0.24
t-statistic	[–1.14]	[–1.31]	[–1.25]	[–1.01]	[–1.07]	[–1.22]	[–1.22]	[–0.92]
BM		0.01	–0.01	0.21		–0.04	–0.03	0.17
t-statistic		[0.09]	[–0.06]	[1.58]		[–0.32]	[–0.22]	[1.31]
ME			–0.02	–0.03			0.02	0.03
t-statistic			[–0.34]	[–0.57]			[0.38]	[0.46]
RU				1.09				1.13
t-statistic				[2.84]				[2.81]

We ultimately assess whether it holds true that matching efficiency shocks carry negative price of risk, again by making use of Fama-MacBeth two-pass regressions. Our findings are depicted in Table VIII and imply no significant relation between loading on estimated shocks to matching efficiency and future equity returns in Sweden. The results from the sub-sample, in which micro-cap firms are excluded, echo the findings from the full sample. These results suggest that the significant four-factor alpha of the low-high portfolio in Table VII is not a result of systematic risk compensation related to search frictions. Similar evidence on the insignificance and relation of loading on matching efficiency shocks to future equity returns is found using estimated shocks estimated from the random matching function.[9]

[9] See Appendix D for empirical evidence.

4.3 The Cyclicality of Firm Labor Decisions

If firms' return sensitivity to time-varying matching efficiency is a determinant of the cross-section of stock returns, and if it is due to compensation for differences in labor risk, we would expect firms' loadings on labor search frictions to say something about the cyclicality of their labor decisions. More specifically, firms with positive (negative) loadings would have pro-cyclical (counter-cyclical) labor decisions with respect to matching efficiency.

Our asset pricing test results in Section 4.1.2 and 4.2.2 suggest that firms' return sensitivity to search frictions is not systematically compensated for in the cross-section. We can rationalize these results in two ways. Firstly, it could be that the difference in loadings does not correspond to a systematic difference in firms' labor decisions. This signifies that firms act homogenously, irrespectively of their loadings, such that there is no distinct source of difference in labor risk that can be subject to compensation. Alternatively, heterogeneity in the cycles of firms' labor decisions prevails but it does not imply a difference in riskiness that is systematically priced.

To shed light on potential underlying reasons for our empirical results, we measure unconditional time-series correlations of firms' labor characteristics to labor search friction proxies. To enhance the quality of the correlations, we require each stock included in the decile portfolios to have more than five years of data on said labor characteristics. Labor characteristics include employee growth rates (EGR), wages (WAGE), profitability (PROF), and labor share (LS).

We acknowledge that it would arguably have been more appropriate to allow for correlations to vary over time, seeing as the estimated search friction loadings are time-varying. However, since our labor characteristics are yearly and the number of observations are few, we are unable to meaningfully compute conditional correlations.

If firms' loadings on search frictions serve to proxy for the cyclicality of firm labor decisions, we would expect correlations to systematically increase with loadings for employee growth rates, wages, and profitability, while conversely decrease for labor share. This would then be in tandem with the findings in the U.S. by Kuehn et al. (2017). Our results are depicted in Table IX.

Table IX: The Cyclicality of Firm Labor Decisions

The table depicts mean unconditional time-series correlations for selected decile portfolios as well as for the low-high portfolio. Correlations are between firm characteristics and the labor market tightness factor, and between firm characteristics and estimated matching efficiency shocks, over the period 1983 to 2016 and 1992 to 2016, respectively. The portfolios are formed in June of year *t* on the basis of their loading as of May of year *t*, and held without rebalancing from July of year *t* to June of year *t+1* before being reformed. Matching efficiency shocks are estimated from the stock-flow matching function.

Decile	EGR	WAGE	PROF	LS
Correlation with the labor market tightness factor				
Low	0.11	–0.03	0.11	–0.02
Decile 5	0.07	–0.02	0.18	0.01
High	0.13	–0.05	0.20	–0.08
Low-high	–0.02	0.02	–0.09	0.05
Correlation with estimated matching efficiency shocks				
Low	–0.04	0.03	0.08	0.04
Decile 5	0.02	0.02	0.13	0.06
High	–0.01	0.00	0.11	0.01
Low-high	–0.03	0.03	–0.03	0.03

In the case of the labor market tightness factor, we cannot establish any systematic pattern in correlations of EGR, WAGE, and LS across the decile portfolios. Furthermore, our results signify low discrepancy in cyclicality of aforementioned metrics. The cyclicality of PROF to the labor market tightness factor is, however, increasing with loading. This is somewhat expected, given that returns, on which loadings are based, are strongly related to profitability.

A similar story is told in the case of estimated matching efficiency shocks. We observe a difference in the cyclicality of EGR between the low- and high decile portfolios but fail to establish a conclusive pattern. Moreover, EGR is negatively correlated with estimated matching efficiency shocks for both the low- and high decile portfolio – directly contradicting the notion that hiring policies of highly loaded firms are pro-cyclical to matching efficiency.

The correlation of PROF tend to increase with loading, suggesting that firms' return sensitivities, at least to some extent, capture how their productivity vary. Conversely, the cyclicality of firms' labor characteristics is seemingly independent from loadings. Consequently, while there is some heterogeneity in the cyclicality of firms' returns, the corresponding discrepancy between firms' labor decision cyclicality is small. That is, there is no apparent source of systematic difference in undertaken risk stemming from differing labor decision cyclicality between lowly- and highly loaded firms.

4.4 Law of Motion for Labor Market Tightness

Drawing on the notion that the labor market tightness factor (Section 4.1.1) and the estimated matching efficiency shocks (Section 4.2.1) essentially serve to capture equivalent labor dynamics, we would expect them to yield similar asset pricing results. To investigate if this holds true, we match the considered time period for the labor market tightness factor to that of the estimated matching efficiency shocks, and subsequently plot the cumulative log return of each low-high portfolio in Figure 4.

Figure 4: Contrasting Cumulative Log Return of Low-High Portfolios. This figure depicts the cumulative log return of the low-high portfolio loading on the labor market tightness factor (black line) and the estimated matching efficiency shocks (gray line), respectively. The data is monthly. The time period is July 1995 to December 2016.

We observe large differences in the behavior of the cumulative returns of the two low-high portfolios. Building on this discrepancy, we investigate the correlation between the two different low-high portfolio returns, and we also look to the correlation between the labor market tightness factor and the estimated matching efficiency shocks. The findings are captivating, as they point to a correlation of 0.08 and –0.06 for the low-high portfolio returns and search friction proxies, respectively.

To statistically verify our findings, we investigate whether the law of motion defined in Equation 1 holds true in Sweden. Using an ordinary least squares regression, we assess the relation between labor market tightness (θ_t), estimated matching efficiency shocks (ρ_t), and industrial production (IP_t) which proxy for total factor productivity. Moreover, we control labor market tightness for autocorrelation with one lag (θ_{t-1}). The regression is expressed in Equation 13

$$\log(\theta_t) = \alpha_0 + \beta_1 \log(\theta_{t-1}) + \beta_2 \Delta \log(\mathrm{IP}_t) + \beta_3 \rho_t + \varepsilon_t. \tag{13}$$

The results from the regression are in support of our previous findings. Namely, it states a negative relation of –0.07 between labor market tightness and the estimated matching efficiency shocks. This negative point estimate is, however, not significantly different from zero (t-statistic –1.12). Conversely, the industrial production point estimate is positive at 0.41 and weakly significant (t-statistic 1.79).

In the two-factor model presented by Kuehn et al. (2017), shocks to aggregate matching efficiency and productivity are mapped onto labor market tightness and the market return, respectively. Our results in this section, however, shed doubt on the ability of labor market tightness to capture matching efficiency shocks in Sweden. This inability could arguably be linked to the findings made in Table V, in which it is evidenced that labor flows are important in explaining the Swedish job matching process. Accordingly, as said labor dynamics are not fully captured by changes in the vacancies-to-unemployment ratio, it follows that the ability of the labor market tightness factor to serve as a proxy for search frictions is impaired.

5 Discussion

Our empirical findings differ from that of the comparable research paper with regards to the cyclicality of firms' labor decisions across loadings on matching efficiency, and the ability of labor market tightness to capture shocks to matching efficiency. Discrepancies prevail between nations' labor markets and we argue that it translates into differing firm labor decisions across countries, which subsequently has implications for production-based asset pricing. To build on this, we make use of previous literature suggesting that firms' hiring costs are two-fold, pre- and post-match, and that the share of said components in total hiring costs is crucial for the propagation of matching efficiency shocks (Furlanetto and Groshenny, 2016). The pre-match component signifies search costs of advertising vacancies while the post-match component corresponds to the cost of adjusting the hiring rate.

In a setting of substantial post-match costs, firms are incentivized to uphold a stable hiring rate to avoid costly employment adjustments. A firm's hiring rate can be expressed as a function of the vacancy rate, the probability of filling a vacant position, and the separation rate. The probability of filling vacancies is time-varying and positively (negatively) affected by positive (negative) aggregate shocks to matching efficiency. Firms' mitigate the effects to the hiring rate from matching efficiency shocks by posting less (more) vacancies in times of positive (negative) shocks. They do so as adjusting vacancy postings is relatively inexpensive to employment adjustments. The described behavior among firms affects the correlation between vacancies and matching efficiency negatively. Also, it follows that the hiring rate remains fixed and thus is independent from time-varying matching efficiency.

In the case of Sweden, the nation has more rigorous employee protection laws and organized labor unions as compared to the U.S. The empirically observed insensitivity of Swedish firms' labor decisions to loadings on matching efficiency, as identified in Section 4.3, could then arguably be the result of a high share of post-match costs in total hiring costs, caused by substantial separation costs. Therefore, Swedish firms strive to hold their hiring rate stable, and additional hiring in times of positive matching efficiency shocks is curbed as firms want to avoid the risk of having to lay off workers in the future. The described behavior signifies that Swedish firms counteract shocks by adjusting vacancy postings, which would be in line with the empirically observed negative relation between excess demand of labor (proxied by labor market tightness) and shocks to matching efficiency in Section 4.4.

Kuehn et al. (2017) present a model in which the effect on labor market tightness of a positive shock to matching efficiency is two-fold and depends on opposing discount- and cash flow effects. In the setting of said model, our rationale implies that the positive cash flow effect of a positive shock to matching efficiency is insufficient to incentivize Swedish firms to deviate from their stabilized hiring rate.

Alternatively, if matching efficiency shocks carry negative price of risk, the higher required rate of return in times of positive shocks could partly or fully offset the positive cash flow effect. This opposing discount effect would then also, similarly to an insufficient cash flow effect, explain why Swedish firms' labor decisions are not affected by shocks to matching efficiency. However, since the notion of a negative price of risk for shocks to matching efficiency in Sweden is not supported empirically (see Section 4.2.2), we deem the discount effect to be negligible and hence disregard from considering it as part of our rationalization.

6 Conclusion & Future Research

This paper investigates labor search frictions and the implications for cross-sectional stock returns in Sweden. Using the labor market tightness factor as proxy for time-varying aggregate matching efficiency, we are unable to establish a significant relation between firms' loadings on said factor and future equity returns. We extend the analysis further, substituting the labor market tightness factor for matching efficiency shocks estimated from aggregate matching functions, and find similar evidence. Moreover, we find that Swedish firms sorted by their loadings do not systematically differ in how their labor-related characteristics correlate with matching efficiency, and that the labor market tightness factor is not significantly related to matching efficiency shocks.

Our empirical findings differ to the comparable study by Kuehn et al. (2017) on the U.S. To explain this discrepancy, we build on the notion that Swedish firms face higher job separation costs compared to U.S. firms. This renders them less willing to deviate from their hiring rate, irrespective of time-variations in matching efficiency. Therefore, Swedish firms' hiring policies are exposed fairly homogenously to search frictions and consequently there is no systematic compensation in the cross-section.

The evidence put forward in this study should not be considered as critique of related literature. Instead, it provides insight into how differences in labor market dynamics affect the propagation of matching efficiency shocks into firms' labor decisions. Ultimately, this has consequences for the link between search frictions and cross-sectional equity returns, as well as for the ability of the labor market tightness factor to serve as a reliable proxy for matching efficiency shocks.

Due to data limitations, this paper considers a substantially shorter time period compared to the U.S. study. Therefore, to strengthen the notion of labor market dynamics having implications for the relation between search frictions and asset prices, we suggest further research to be made on longer time-series data and on additional nations. Moreover, it is assumed in this paper that all Swedish firms are exposed to the aggregate Swedish time-varying matching efficiency. This is a simplification for several reasons. Namely, there might prevail regional differences in the domestic matching efficiencies and, moreover, firms might hire employees outside of Sweden. Hence, future research could aim to better capture firms' true search friction exposures so as to more distinctly link search frictions to asset pricing.

7 References

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A Derivation of Aggregate Matching Functions

A matching function relates the number of jobs created (M_t) to that of the number of unemployed looking for work (U_t), and the number of vacant positions (V_t)

$$M_t = f(U_t, V_t). \tag{14}$$

Under random matching, the unemployed job seekers are matched, and the vacancies are filled, at Poisson rates $\lambda_{U_t} = \frac{M_t}{U_t}$ and $\lambda_{V_t} = \frac{M_t}{V_t}$. Matches during a period of length one is given by

$$M = \int_0^1 m(U_t, V_t)\mathrm{d}t = \int_0^1 U_t \lambda_{U_t} \mathrm{d}t, \tag{15}$$

whereby U_t is defined as

$$U_t = U_0 \exp\left(-\int_0^t \lambda_{U_s}\,\mathrm{d}s\right) + \int_0^t u_{t'} \exp\left(-\int_{t'}^t \lambda_{U_s} \mathrm{d}s\right) \mathrm{d}t'. \tag{16}$$

U_0 is the stock of unemployed at the beginning of the period, and u_t is the inflow of unemployed over the period. To estimate Equation 16 one needs to make an assumption regarding the evolution of u_t and λ_{U_t} within the period. Assuming an uniform inflow of unemployed, and that the exit rate is constant, so that $u_t = u$ and $\lambda_{U_t} = \lambda_U$, the number of matches is defined as

$$M = \left(1 - e^{-\lambda_U}\right)U_0 + \left(1 - \frac{1-e^{-\lambda_U}}{\lambda_U}\right). \tag{17}$$

Stock-flow matching captures a realistic feature of the labor market, namely that job seekers scan an extensive amount of vacancies before applying, and that newly unemployed job seekers firstly review and apply for the existing stock of vacancies. Those who do not match immediately will in subsequent periods only sample inflows of vacancies, since the stock has already been reviewed and rejected. To model this process, the probability of matching directly is denoted p_u, so that with probability $1 - p_u$ unemployed job seekers will have to wait to match with the inflow of vacancies at Poisson rate λ_U. The number of matches under stock-flow matching is given by

$$M = \left(1 - e^{-\lambda_U}\right)U_0 + \left[1 - \frac{1-p_u}{\lambda_U}\left(1 - e^{-\lambda_U}\right)\right] u. \tag{18}$$

B Variable Definitions

The stock return in month *t* is the change of the last traded price from end of month *t-1* to end of month *t*, measured using simple returns. In the instance of an unavailable last price, we use mid-price instead.

Book value of equity (BE) is the equity attributable to equity holders in the parent company. Market equity (ME) is the sum of each stock class' bid price times the number of shares in the stock class less the shares held by the company (treasury shares). Book-to-market (BM) is then the ratio of the aforementioned values (BE/ME). In Fama-MacBeth (1973) regressions, BM in January to June of year *t* uses the BE for the fiscal year-end in *t-2*, while the BM in July to December of year *t*, uses BE for the fiscal year-end in *t-1*. This is to insure that the accounting metric is known before the returns it is used to explain.

RU is the 12-month stock return run-up, and is defined as $\prod_{\tau=1}^{12}\left(1+R_{i,t-\tau}\right)-1$. AG is the asset growth rate, and is calculated as $\frac{A_t}{A_{t-1}}-1$, where A_t is the total value of assets for the fiscal year-end in *t*. IK is the investment rate, and is calculated as capital expenditures in fiscal year *t* divided by the lagged value of total assets ($\frac{Capex_t}{A_{t-1}}$). HN is the hiring rate, and is defined as $\frac{(N_t-N_{t-1})}{((N_t+N_{t-1})/2)}$, where N_t is the number of employees for the fiscal year-end in *t*. LEV is the leverage, and is calculated as total debt for the fiscal year-end in *t* divided by total assets ($\frac{D_t}{A_t}$).

EGR is the employee growth rate, and is calculated as $\frac{N_t}{N_{t-1}}-1$. WAGE is the average yearly wage, defined as salaries and benefits expenses, divided by the lagged number of employees ($\frac{W_t}{N_{t-1}}$). PROF is profitability and is calculated as net income in fiscal year *t* divided by net sales in fiscal year *t* ($\frac{NI_t}{Sales_t}$). LS is the labor share, and is obtained by dividing salaries and benefits expenses with net sales ($\frac{W_t}{Sales_t}$).

C SPES Labor Statistics

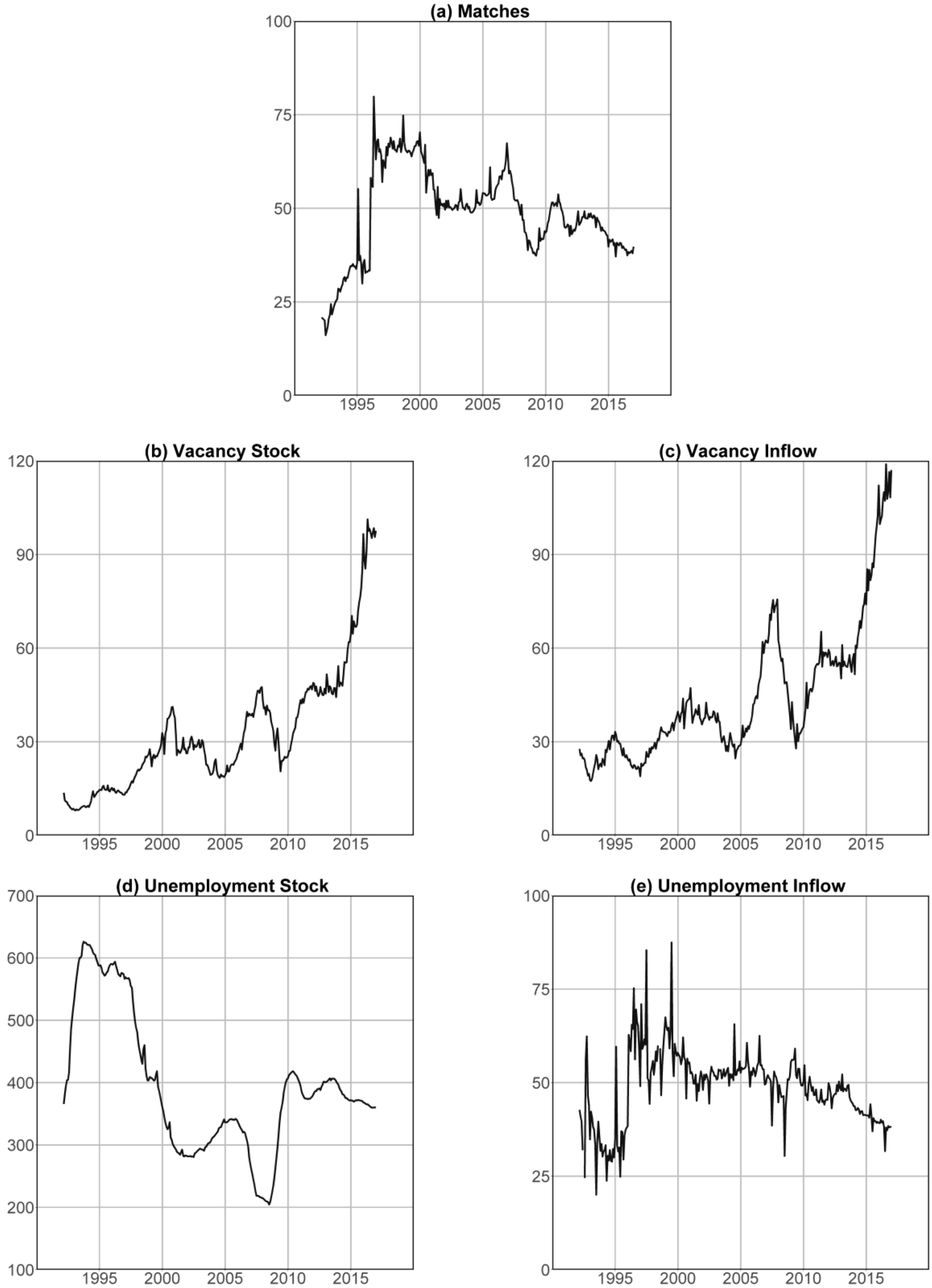

Figure 5: SPES Labor Statistics. This figure depicts seasonally adjusted time-series of the underlying labor data used in the aggregate matching functions; matches (a), vacancy stock (b), vacancy inflow (c), unemployment stock (d), and unemployment inflow (e). All time-series are expressed in thousands. The data is monthly and span over the period January 1992 to December 2016.

D Tests Using Random Matching Shocks

Table X: Characteristics of Matching Efficiency Shock Decile Portfolios

This table contains mean characteristics for portfolios of stocks sorted by their loadings on estimated matching efficiency shocks (β^{ρ}). β^{M} is the market beta, BM the book-to-market ratio, and ME the market equity decile. RU is the 12-month run-up return, AG the asset growth rate, IK the investment rate, HN the new hiring rate, and LEV is the leverage, all in percent. Portfolios are formed in June of year *t* on the basis of their loading as of May of year *t*, and held without rebalancing from July of year *t* to June of year *t+1* before being reformed. Matching efficiency shocks are estimated from the random matching function, no adjustment is made for autocorrelation in the residuals. Mean characteristics are calculated annually and then averaged over time. The period is July 1995 to December 2016.

Decile	β^{ρ}	β^{M}	BM	ME	RU	AG	IK	HN	LEV
Low	–0.35	1.00	0.86	4.47	21.90	9.94	5.80	3.33	20.62
2	–0.19	0.92	0.72	5.76	18.55	5.94	3.96	5.47	17.62
3	–0.12	0.88	0.71	5.79	22.15	35.15	4.36	7.65	20.90
4	–0.06	0.91	0.75	6.01	19.30	9.98	5.39	2.37	20.53
5	–0.01	1.01	0.74	6.02	17.73	9.96	5.00	3.02	21.01
6	0.03	1.10	0.70	6.10	20.72	9.52	3.82	3.43	20.70
7	0.08	0.98	0.76	5.72	18.90	8.12	4.17	0.73	18.77
8	0.14	0.95	0.74	5.61	16.63	11.91	5.49	4.91	17.22
9	0.23	1.22	0.70	5.08	16.69	9.06	4.87	2.18	19.67
High	0.42	1.27	0.66	4.27	19.64	22.97	4.82	4.86	15.11

Table XI: Performance of Matching Efficiency Shock Decile Portfolios

This table reports average monthly raw returns and unconditional alphas, in percent, and four-factor loadings for the 10 portfolios of stocks sorted by their loading on estimated matching efficiency shocks, as well as for the low-high β^{ρ} portfolio. The value-weighted portfolios are formed in June of year *t* on the basis of their loading as of May of year *t*, and held without rebalancing from July of year *t* to June of year *t+1* before being reformed. Matching efficiency shocks are estimated from the random matching function, no adjustment is made for autocorrelation in the residuals. The bottom row contains *t*-statistics for the low-high portfolio. The period is July 1995 to December 2016.

	Raw	Unconditional Alpha			FF4-Loadings			
Decile	Return	CAPM	FF3	FF4	MKT	SMB	HML	MoM
Low	2.07	0.86	0.85	0.92	1.25	0.38	0.24	–0.12
2	1.06	0.16	0.03	0.07	0.84	0.00	0.22	–0.06
3	1.44	0.57	0.39	0.38	0.84	–0.03	0.31	0.01
4	1.37	0.38	0.31	0.35	0.93	0.06	0.18	–0.07
5	1.49	0.49	0.42	0.37	0.98	–0.01	0.11	0.09
6	0.62	–0.55	–0.57	–0.56	1.11	0.00	0.04	–0.02
7	1.68	0.61	0.65	0.64	0.98	0.01	–0.08	0.02
8	0.77	–0.25	–0.41	–0.40	1.00	–0.02	0.27	–0.01
9	1.04	0.01	0.08	0.10	0.92	0.07	–0.08	–0.04
High	0.87	–0.32	–0.20	–0.16	1.11	0.18	–0.11	–0.07
Low-high	1.20	1.18	1.05	1.08	0.14	0.21	0.35	–0.05
t-statistic	[2.37]	[2.29]	[2.07]	[2.11]	[1.41]	[1.86]	[3.25]	[–0.63]

Table XII: Fama-MacBeth Regressions of Monthly Stock Returns

This table depicts the results of Fama-MacBeth (1973) regressions of monthly stock returns on lagged loadings on estimated matching efficiency shocks (β^{ρ}), market betas (β^{M}), log market equity (ME), log book-to-market (BM), and 12-month run-up returns (RU). Matching efficiency shocks are estimated from the random matching function, no adjustment is made for autocorrelation in the residuals. Average coefficients and Newey-West (1987) *t*-statistics are reported. The period is March 1995 to December 2016.

	Full Sample				Excluding Micro Cap			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
β^{ρ}	–0.54	–0.30	–0.34	–0.38	–0.23	–0.22	–0.14	–0.21
t-statistic	[–1.26]	[–0.73]	[–0.84]	[–0.94]	[–0.51]	[–0.52]	[–0.33]	[–0.51]
β^{M}	–0.25	–0.28	–0.27	–0.21	–0.26	–0.28	–0.30	–0.23
t-statistic	[–0.94]	[–1.08]	[–1.03]	[–0.85]	[–0.90]	[–1.05]	[–1.10]	[–0.90]
BM		0.00	0.00	0.21		–0.05	–0.02	0.15
t-statistic		[0.03]	[0.02]	[1.63]		[–0.37]	[–0.17]	[1.16]
ME			–0.01	–0.02			0.04	0.04
t-statistic			[–0.08]	[–0.32]			[0.62]	[0.58]
RU				1.03				0.99
t-statistic				[2.71]				[2.45]

Table XIII: The Cyclicality of Firm Labor Decisions

The table depicts mean unconditional time-series correlations for selected decile portfolios as well as for the low-high portfolio. Correlations are between firm characteristics and estimated matching efficiency shocks, over the period 1992 to 2016. The portfolios are formed in June of year *t* on the basis of their loading as of May of year *t*, and held without rebalancing from July of year *t* to June of year *t+1* before being reformed. Matching efficiency shocks are estimated from the random matching function, no adjustment is made for autocorrelation in the residuals.

Decile	EGR	WAGE	PROF	LS
Correlation with estimated matching efficiency shocks				
Low	–0.02	0.03	–0.03	0.14
Decile 5	0.02	0.08	0.04	0.10
High	0.01	0.06	–0.02	0.14
Low-high	–0.02	–0.02	–0.01	0.00