

Labor Hiring, Aggregate Dividends, and Return Predictability in the Time Series^{*}

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ABSTRACT

Using a standard production model, we demonstrate theoretically that (a) aggregate hiring rates negatively predict aggregate discount rates *and* dividends (b) large firms explain most of return predictability while small firms explain most of the dividend predictability and (c) the explanatory power of hiring rates is not explained by traditional cash-flow based measures of performance. We present evidence for the three predictions of our model, and demonstrate the significance of labor hiring to understand the dynamic nature of discount rates and cash flows.

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If today prices are high relative to dividends, then, unless future dividend growth is higher than usual, future returns will be lower than usual. This well-established idea, which was formalized in Shiller’s seminal (1981) paper, implies that discount rates or cash flow growth—or a combination of the two—should be predictable. Extensive research studies the predictive power of many variables. The accumulated body of evidence now provides evidence in favor of discount rate predictability and strongly against cash flow growth predictability. However, less attention was given to the study of the predictive power of labor market variables. In this paper, we help close this gap and provide theoretical and empirical evidence that hiring rates *negatively* predict discount rates *and* cash flow growth remarkably well. In particular, our paper shows that the hiring activity of large firms, low beta firms, and publicly listed firms better predicts changes in aggregate discount rates, even though these firms are less exposed to systematic shocks.

In many—if not most—existing asset pricing models, firms’ hiring and firing activity only responds to shocks to present cash flows and is thus unable to predict shocks to discount rates. It is the presence of adjustment costs and other labor demand frictions that make hiring and firing decisions forward looking and informative about discount rate and *future* cash flows.¹ For instance, when discount rate falls, the marginal benefit of labor to firm value increases which motivates the firm to hire more workers. Therefore, hiring should negatively predict discount rate and positively predict expected cash flows. Consistent with this intuition, Belo, Lin, and Bazdresch (2014) show that hiring rates do negatively predict returns in the cross-section. At the aggregate level, however, Chen and Zhang (2011) find little evidence that hiring can predict risk premium.

In this paper, we present evidence that the lack of predictive power of aggregate hiring rates is fully explained by the hiring decisions of privately held firms. We present novel evidence that hiring activity in the sample of public firms in the economy does predict changes in discount rates remarkably, even in out-of-sample tests.

¹See for example Merz and Yashiv (2007) for an early discussion of this idea.

We present evidence for the hypothesis that the average size difference between private and public firms helps explain almost all of the different predictive power of their hiring rates. We present a simple production-based asset pricing model that shows why small firms are less responsive to changes in discount rates than large firms, even though these firms are more exposed to systematic risk. We verify this model prediction empirically through in-sample and out-of-sample tests.

Our work contributes to our understanding about the relationship between labor income and asset returns. This literature goes as far back as Mayers (1973) and Fama and Schwert (1977).² Within this literature, our work is more closely related to the strand that focuses on the time-series predictability of aggregate market returns by labor market variables. A few examples of labor-related variables studies in this literature are aggregate labor share (e.g., Danthine and Donaldson (2002)), fixed-to-variable compensation ratio (e.g., Parlour and Walden (2011)), aggregate labor mobility (e.g., Donangelo, Eiling, and Palacios (2010)), organization capital (e.g., Eisfeldt and Papanikolaou (2013)), labor market tightness (e.g., Petrosky-Nadeau, Zhang, and Kuehn (2013)), investments in human capital (e.g., Palacios (2015)), and wage rigidity (e.g., Uhlig (2007) and Favilukis and Lin (2016)). In a closely related paper, Chen and Zhang (2011) show that search frictions generate a bidirectional link between aggregate labor hiring and expected returns. We contribute to this literature by showing that the *distribution* of hiring rates in the economy provide additional theoretically motivated labor market characteristics that help explain time variation in aggregate market returns.

By exploring cross-sectional differences in hiring rates to predict aggregate market returns, our work also contributes to the literature that studies the relation between firm level labor characteristics and stock returns. Some examples of characteristics studied by this literature are (cross-sectional heterogeneity in) labor-capital complementarity (e.g., Gourio (2007) and Donangelo, Gourio, and Palacios (2016)), share of

²More recent work includes Campbell (1996), Boyd, Hu, and Jagannathan (2005), Santos and Veronesi (2006), Lustig and Van Nieuwerburgh (2008), and Lettau, Ludvigson, and Ma (2014).

skilled labor (e.g., Ochoa (2013) and Belo, Lin, Li, and Zhao (2015)), labor mobility (e.g., Donangelo (2014)), wage high-water mark (e.g., Zhang (2014)), share of routine labor (e.g., Zhang (2015)), and firm’s exposure to labor market tightness (e.g., Kuehn, Simutin, and Wang (2016)). Within this literature, our paper is most closely related to Belo et al. (2014) who show that cross-sectional heterogeneity in hiring rates helps explain the cross-section of expected returns. Our work also contributes to the broad asset pricing literature that studies the relation between firm characteristics and the cross-section of returns.³

Our work also relates to the broad literature that studies the predictability of aggregate market returns and cash flows.⁴ And finally, the theoretical approach in this paper is related to the broad literature that studies asset prices in production economies.⁵

The paper proceeds as follows. Section I presents a simple neoclassical production model to formalize our testable hypotheses and guide our empirical analysis. Section II formalizes the testable hypotheses and describes the financial and labor market data used to test them. Section III presents our main empirical findings. Finally, Section IV concludes.

I. A Simple Model of Adjustment Costs

In this section, we develop and provide theoretical motivation for the main hypothesis of our empirical tests. To establish the theoretical link between labor hiring predictability and aggregate stock returns and dividends, we extend the model in Belo et al. (2014) (henceforth BLB) who consider an economy with labor market frictions:

³See Fama and French (2008) and Harvey, Liu, and Zhu (2014) for surveys of this literature.

⁴Some examples of this literature are Campbell and Shiller (1988), Fama and French (1988), Hodrick (1992), Cochrane (2008), and Kelly and Pruitt (2013).

⁵A non-comprehensive list of studies includes Berk, Green, and Naik (1999), Kogan (2001), Kogan (2004), Carlson, Fisher, and Giammarino (2004), Zhang (2005), Livdan, Sapriz, and Zhang (2009), Tuzel (2010), Imrohoroglu and Tuzel (2014), Kogan and Papanikolaou (2013), and Kogan and Papanikolaou (2014).

labor hiring and firing is costly for firms, which is captured through an adjustment cost function.

A. *Economic Environment*

There is a large number of firms in the economy that produce a homogeneous good.

A.1. *Technology*

We focus on the optimal production decision problem of one firm in the economy (we omit any firm-specific subscripts to save on notation). The firm uses labor inputs N_t to produce output Y_t , according to the following constant technology:

$$Y_t = Z_t X_t N_t^\alpha, \quad (1)$$

in which $0 < \alpha < 1$ controls the degree of returns to scale. X_t is aggregate productivity, and $Z_{t,i}$ is firm-specific productivity, the source of cross-sectional heterogeneity.

The law of motion of the firm's total labor force N_t is given by

$$N_{t+1} = (1 - \delta_n)N_t + H_t \quad 0 < \delta_n < 1, \quad (2)$$

in which δ_n is the (constant) quit rate, the rate at which workers leave the firm for voluntary reasons, and H_t is gross hires, which can be positive (hire) or negative (fire).

Labor hiring and firing is subject to adjustment costs. For simplicity, we assume the following quadratic adjustment cost function:

$$CN_t^{\text{adj}} = \frac{c_n}{2} \left(\frac{H_t}{N_t} \right)^2 N_t \quad (3)$$

in which $c_n > 0$ is a constant that controls the size of labor adjustment costs.

Finally, the firm also incurs fixed operating costs of production that are independent of firm size, which are captured by the parameter $f > 0$.

A.2. Firm's Maximization Problem

Firms are competitive and take prices (stochastic discount factor $M_{t,t+1}$, as well as the equilibrium stochastic wage rate, W_t) as given. Following Zhang (2005), we directly specify the stochastic discount factor without explicitly modeling the consumer's problem. The stochastic discount factor is given by:

$$\log M_{t,t+1} = \log \beta + \gamma_t(x_t - x_{t+1}) \quad (4)$$

$$\gamma_t = \gamma_0 + \gamma_1(x_t - \bar{x}), \quad (5)$$

where $M_{t,t+1}$ denotes the stochastic discount factor from time t to $t+1$. The parameters $\{\beta, \gamma_0, \gamma_1\}$ are constants satisfying $1 > \beta > 0$, $\gamma_0 > 0$ and $\gamma_1 < 0$. According to this specification, the risk-free rate ($R_{f,t}$) and the maximum Sharpe ratio (SR_t) in the economy are given by:

$$R_{f,t} = \frac{1}{E_t[M_{t,t+1}]} = \frac{1}{\beta} e^{-\gamma_t(1-\rho_x)(x_t - \bar{x}) - \frac{1}{2}\gamma_t^2\sigma_x^2} \quad (6)$$

$$SR_t = \frac{\sigma_t[M_{t,t+1}]}{E_t[M_{t,t+1}]} = \sqrt{e^{\gamma_t^2\sigma_x^2} - 1}. \quad (7)$$

Equation (7) can be motivated as a reduced-form representation of the intertemporal marginal rate of substitution for a fictitious representative consumer or the equilibrium marginal rate of transformation, as in Belo (2010). According to equation (5), γ_t is time varying and decreases in the demeaned aggregate productivity shock $x_t - \bar{x}$ to capture the well-documented countercyclical price of risk with $\gamma_1 < 0$. The precise economic mechanism driving the countercyclical price of risk can be, for example, time-varying risk aversion, as in Campbell and Cochrane (1999).

The real wage rate is an increasing function of the aggregate productivity, and is given by

$$W_t = \tau_1 \exp(\tau_2 x_t), \quad (8)$$

with $\tau_1, \tau_2 > 0$. In this specification, τ_1 is a scaling factor, and the parameter τ_2

controls the cyclicality and volatility of the wage rate.

All firms in the economy are assumed to be all-equity financed, so we define

$$D_t = Y_t - W_t N_t - C N_t^{\text{adj}} - f \quad (9)$$

to be the dividend distributed by the firm to the shareholders. The dividend consists of output Y_t , less the wage bill $W_t N_t$, labor adjustment costs $C N_t^{\text{adj}}$, and fixed operating costs f . A negative dividend is considered as an equity issuance.

Define the vector of state variables as $\mathbb{S}_t = (N_t, x_t, z_t)$, and let $V(\mathbb{S}_t)$ be the cum-dividend market value of the firm in period t . The firm makes hiring H_t decisions to maximize its cum-dividend market value by solving the problem

$$V(\mathbb{S}_t) = \max_{\{H_{t+j}, N_{t+j+1}\}_{j=0}^{\infty}} \left\{ \mathbb{E}_t \left[\sum_{j=0}^{\infty} M_{t,t+j} D_{t+j} \right] \right\}, \quad (10)$$

subject to the labor accumulation equation (2), and the flow of funds constraint (9) for all dates t .

B. Calibration

All the endogenous variables in the model are functions of the state variables. Because the functional forms are not available analytically, we solve for these functions numerically. We calibrate the model at the monthly frequency using the parameter values reported in Table I. The share of labor expenses on output, α , is 0.72, following Imrohoroglu and Tuzel (2014). The monthly labor quit rate, δ_n , is 0.018, which matches the 1.8% average aggregate worker quit rate from JOLTS (Job Openings and Labor Turnover Survey) sample from Dec 2000 to Dec 2015. The persistence and conditional volatility of aggregate uncertainty, ρ_x and σ_x , are taken from the quarterly calibration of Cooley and Prescott (1995), and set to be 0.983 ($0.95^{1/3}$) and 0.004 ($0.007/\sqrt{3}$), respectively. The persistence and conditional volatility of idiosyncratic uncertainty, ρ_z and σ_z , are set to be 0.97 and 0.1 following Zhang (2005). Wage pa-

parameters τ_1 and τ_2 are 1 and 0.2 following Imrohoroglu and Tuzel (2014) to match the aggregate wage cyclicality in the data. The labor adjustment cost parameter, c_n is 11.6, matching 26% time series volatility of firm hiring rates as shown in Belo et al. (2014). The pricing kernel parameters β , γ_0 , and γ_1 are chosen to match the mean risk-free rate and the mean and volatility of aggregate value-weighted excess stock returns. The time discount factor β is 0.999, which implies an annual risk free rate of 1.2%. Constant part of price of risk γ_0 and time varying part price of risk γ_1 are 3.17 and -22, jointly matching 7% mean and 17% standard deviation of annual excess stock return. The model is simulated at monthly frequency and aggregated into annual frequency.

Table I
Baseline Parameter Values

This table shows the parameter values obtained in the monthly model calibration.

Parameter	Symbol	Value
Labor production share	α	0.72
Labor quit rate	δ_n	0.018
Labor adjustment cost	c_n	11.6
Fixed operating cost	f	0.01
Time discount factor	β	0.999
Constant part price of risk	γ_0	3.17
Time varying part price of risk	γ_1	-22
Wage constant	τ_1	1
Wage sensitivity to aggregate productivity	τ_2	0.2
Conditional volatility of aggregate uncertainty	σ_x	0.004
Persistence of aggregate uncertainty	ρ_x	0.983
Conditional volatility of firm productivity	σ_z	0.1
Persistence of firm uncertainty	ρ_z	0.97

Table II reports the summary statistics of samples of firms sorted on employment from simulated data generated by the model. The table shows that the model matches well selected moments of real quantities of a small and large firm in the economy.

Table II
Summary Statistics of Panel of Simulated Firms

This table reports the average portfolio characteristics of low and high employment firms in the simulated model.

	Low Emp.	High Emp.
N: Employees	0.18	1.00
R ^e (%)	13.10	7.11
Mean HN (%)	15.9	-0.30
S.D. HN (%)	4.61	1.84
Market Equity	3.19	5.20
Market Beta (β)	1.06	0.99

II. Empirical Strategy

A. Testable Predictions

The goal of the theoretical analysis is to establish a link between hiring, aggregate risk premiums, and aggregate dividends in the time series. In addition, we investigate how this link varies across firms of different size. To the extent that small and large firms have different levels of risk, the link between their hiring decisions and aggregate risks (discount rates) may be different. In particular, due to operating leverage effect, small firms are more sensitive to changes in aggregate risk than large firms.

Table III, reports the model implied predictions for time series predictability of aggregate excess returns and aggregate dividends. To obtain the testable predictions, we use standard (Fama and French (1989); Lettau and Ludvigson (2002)) short- and long-horizon predictive regressions of the form

$$\sum_{h=1}^H y_{t+h} = a + b \text{HN}_t + \varepsilon_{it}, \quad (11)$$

in which $\sum_{h=1}^H y_{t+h}$ is the H -period cumulated value of the predicted variable, and H is the forecast horizon ranging from one year to five years. HN_t is the aggregate hiring rate, computed separately across small firms, and across large firms. The following

Table III
Moments from Model

This table reports selected moments for subsamples of small and large firms from simulated data generated by the model. The moments illustrate the implications of the model for predictability of hiring for stock returns and aggregate dividends across small firms and large firms. The reported statistics for the model are obtained from 100 samples of simulated data, each with 1,000 firms and 50 yearly observations. The model-implied moments are the mean value of the corresponding moments across simulations.

Horizon	Return Predictability		Dividend Predictability	
	R ²	Coef	R ²	Coef
Subsample of Small Firms				
1	0.95	-0.14	0.90	0.19
2	2.45	-0.70	1.31	0.08
3	4.49	-1.31	2.28	0.04
4	5.55	-1.79	2.82	-0.09
5	5.29	-1.90	2.84	-0.24
Subsample of Large Firms				
1	2.30	-1.63	2.40	-0.94
2	2.61	-2.44	5.35	-1.96
3	4.18	-3.90	9.60	-3.04
4	4.79	-4.60	11.51	-3.51
5	5.01	-5.30	11.65	-3.51

variables are considered: (i) $y_t = r_{st} - r_{ft}$, in which r_{st} is the log aggregate stock market return, and r_{ft} is the log risk-free rate; and (ii) $y_t = \Delta d_t$, in which Δd_t is the growth rate of aggregate dividends. For each regression, the table report the slope coefficient b in Equation (11), and the in sample adjusted R^2 .

In what follows, we describe the key predictions from the model for the link between hiring, discount rates, and aggregate dividends.

P1: Aggregate hiring and expected returns are negatively related in the time series

The negative expected return–hiring relationship is a standard result that follows from standard q-theory (see Belo et al. (2014)). Optimal labor hiring by firms is high when the expected future marginal profitability of labor inputs is high, or when the

discount rate (cost of capital), used to value future marginal profitability of labor is low, or both. Thus, the negative link between labor hiring and expected stock returns (risk) is negative, consistent with the evidence in previous studies.

More interesting, the model makes the novel prediction that the link between hiring and aggregate risk premium (as measured by the slopes of the predictability regressions) is stronger in large firms than in small firms which we state as a new prediction.

P2: The predictability of hiring for stock returns, as measured by the regression slope coefficient, is stronger in larger firms (or low market beta firm) than in smaller (high market beta) firms.

To understand this result, note that the firm's first order condition for hiring can be written approximately as:

$$c_n \left(\frac{H_t}{N_t} \right) = \sum_{j=1}^{\infty} \frac{E_t [x_{t+j}]}{(1+r_t)^j} \quad (12)$$

in which x_{t+j} is the marginal benefit at time $t+j$ (marginal product of labor minus wage rate) of hiring one more worker at time t , and r_t is the appropriate risk adjusted discount rate. This equation states that the firm will hire a worker until the marginal cost of hiring a worker is equal to the present value of the marginal benefits of hiring this worker. Naturally, all the variables in this equation are endogenously determined simultaneously in the model. To develop intuition, however, it is useful to assume that cash-flows and discount rate are constant. In this case, we can write equation (12) as

$$c_n \left(\frac{H_t}{N_t} \right) = \frac{X}{r} \quad (13)$$

in which $X = E_t[x_{t+1}]$, which we assume to be positive so that the firm is hiring ($H_t > 0$). Now, consider a CAPM representation of equilibrium expected returns, which implies that the discount rate of the firm is given by $r = \beta E[R_t - R_f]$, in which β is the firm's market beta, and $E[R_t - R_f]$ is the market risk premium ($E[R_t]$ is the expected

return on the market, and R_f is the risk free rate). Rearranging terms in equation (13) we have:

$$E[R_t - R_f] = \frac{X}{\beta c_n} \left(\frac{H_t}{N_t} \right)^{-1}$$

and a first order Taylor expansion around $\frac{H_t}{N_t} = 1$ yields

$$E[R_t - R_f] = \frac{2X}{\beta c_n} - \frac{X}{\beta c_n} \frac{H_t}{N_t}$$

which we can write in a more compact manner as:

$$E[R_t - R_f] = a + b \frac{H_t}{N_t}$$

where $b = -\frac{X}{\beta c_n}$. Thus, all else equal, the slope coefficient is decreasing (in absolute value) in the firm's market beta. Intuitively, this reflects the fact that the equilibrium discount rate of firms with higher market betas are more sensitive to changes in the aggregate risk premium $E[R_t - R_f]$ (recall, $r = \beta E[R_t - R_f]$), leading to a stronger response of hiring to changes in the aggregate risk premium. In turn, this higher sensitivity leads to a smaller (in absolute value) slope coefficient in the return predictability regression using the firm's hiring rate as the predictor. Prediction P2 then follows because large firms have smaller market betas than small firms.

The model has also implications for the link between hiring and aggregate dividends in the time series.

P3: Aggregate hiring and future dividend growth are negatively related in the time series.

P4: The predictability of aggregate dividends is stronger in smaller (high market beta) firms than in larger (low market beta) firms.

In the next sections, we examine the extent to which these predictions are supported in the data.

B. Data

The key variables for the empirical work are aggregate labor hiring rates, and we measure these variables as in Davis, Faberman, and Haltiwanger (2006) and Bloom (2009). The hiring rate is given by

$$HN_t = 2 \left(\frac{N_t - N_{t-1}}{N_{t-1} + N_t} \right) \quad (14)$$

where N_t is employment. By construction, this measure of labor hiring is symmetric around zero and bounded by $\pm 200\%$. We obtain N_t from Compustat and from the Bureau of Labor Statistics Current Employment Statistics (BLS CES). In Compustat, we sum the number of employees (data item EMP) for all firms at each year as aggregate employment (N_t) for public-traded firms. In CES, we use private sector payroll numbers as N_t . We use the difference between CES N_t and Compustat N_t as employment for private (not publicly traded) firms. We use the previous formula to calculate the aggregate hiring rates for Compustat, CES, and private firms. The sample period is from Jan 1963 to Dec 2015.

Monthly stock returns are from the Center for Research in Security Prices (CRSP), and accounting information is from the CRSP/Compustat Merged Annual Industrial Files. We include firms with common shares (shrcd=10 and 11) and firms traded on NYSE, AMEX, and NASDAQ (exchcd=1, 2, and 3). When we contrast Compustat with CES (publicly traded vs publicly traded + private), we include all firms with different fiscal yearend in Compustat. When we construct portfolios, we follow Liu, Whited, and Zhang (2009) and require a firm to have a December fiscal year end in order to align the accounting data across firms ⁶. Besides, we correct for the delisting bias following the approach in Shumway (1997). We use data of aggregate risk premium

⁶We include financials and utilities. The reason is that we observe that financial firms fired many employees and the hiring rate for financial firms drops a lot in the recent great recession. We believe the hiring of financial firms is informative about the aggregate economy and risk premium, especially in financial-economic crisis. But deleting financials and utilities do not affect our results. And the corresponding results are available upon request.

from Kenneth French’s website, and data of aggregate dividends from Robert Shiller’s website.

To study how size affects firm’s hiring decisions to risk premium and cash flows, we classify Compustat firms as large firms and small firms using two methods. For the first method, we sort on firm’s last period EMP and define small firms as EMP below NYSE 20% breakpoint, following the logic of what Fama-French did for market value as size. For the second method, we sort on firm’s past year market beta and define small firms as beta above NYSE 80% breakpoint⁷. Then we calculate portfolio-level aggregate hiring rates and study how they predict aggregate risk premium and dividend growth differently.

C. Descriptive Statistics

Table IV shows the descriptive statistics of hiring rates from Compustat, CES, implied private, and also Compustat sorted size portfolios. Compustat and CES hiring are highly correlated, 0.78. This gives us confidence that CES include most Compustat firms. Compustat firms have higher mean and are more volatile than CES, which is also in Figure 1.

For size portfolios, low EMP and high beta portfolios capture the notion of small firms. They are more volatile and have higher mean than high EMP and low beta portfolios, i.e., large firms. Low EMP (high beta) portfolio has a volatility of 8.15% (5.2%), while the volatility of high EMP (low beta) portfolio is 2.9% (2.79%). Besides, large firms are more correlated with the aggregate Compustat hiring rate. High EMP and low beta firms have correlations of 0.97 and 0.94 to Compustat all firms and 1.00 (due to 2 decimal points) and 0.97 to Compustat Dec fiscal year end firms. The time series of hiring rates of size portfolios are shown in Figure 2 and Figure 3.

⁷Note that market beta is negatively related to size.

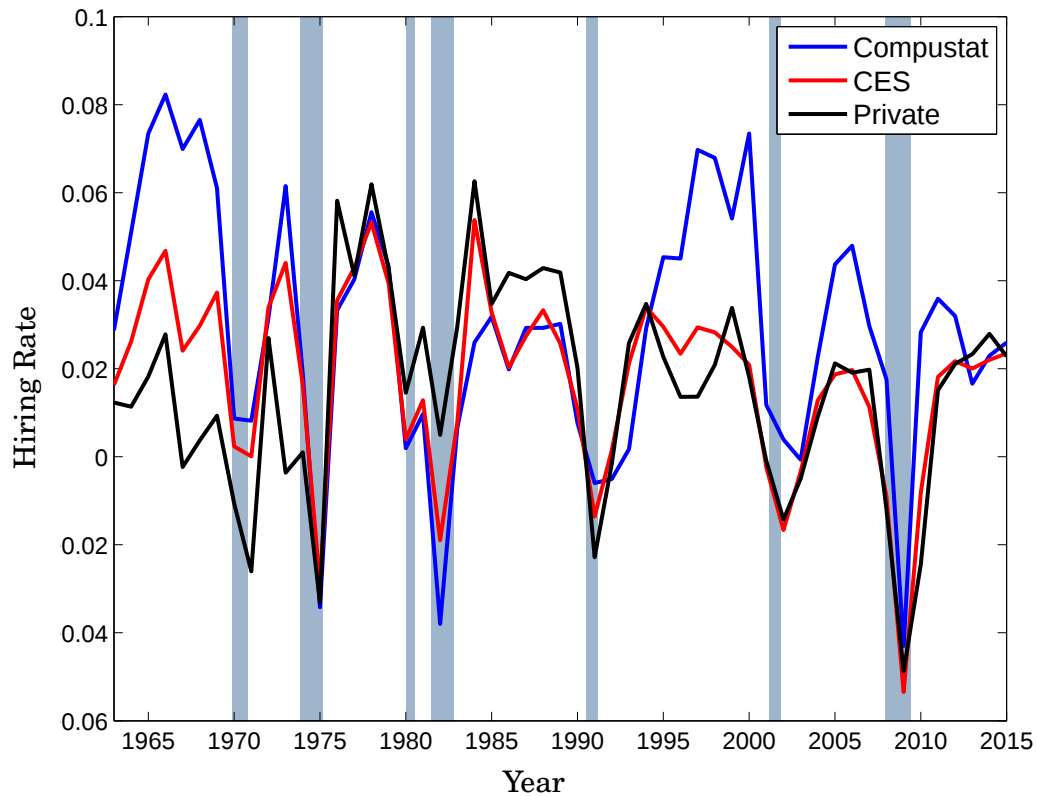


Figure 1. Aggregate Hiring Rates: Public Firms vs Private Firms vs All Firms. This figure shows the aggregate hiring rates from Compustat (i.e., “Public Firms”), from the Current Employment Statistics (CES) and from Bureau of Labor Statistics (i.e., “All Firms”), and from the difference in hiring from all firms minus public firms (“Public Firms”). The sample period is from 1963 to 2015.

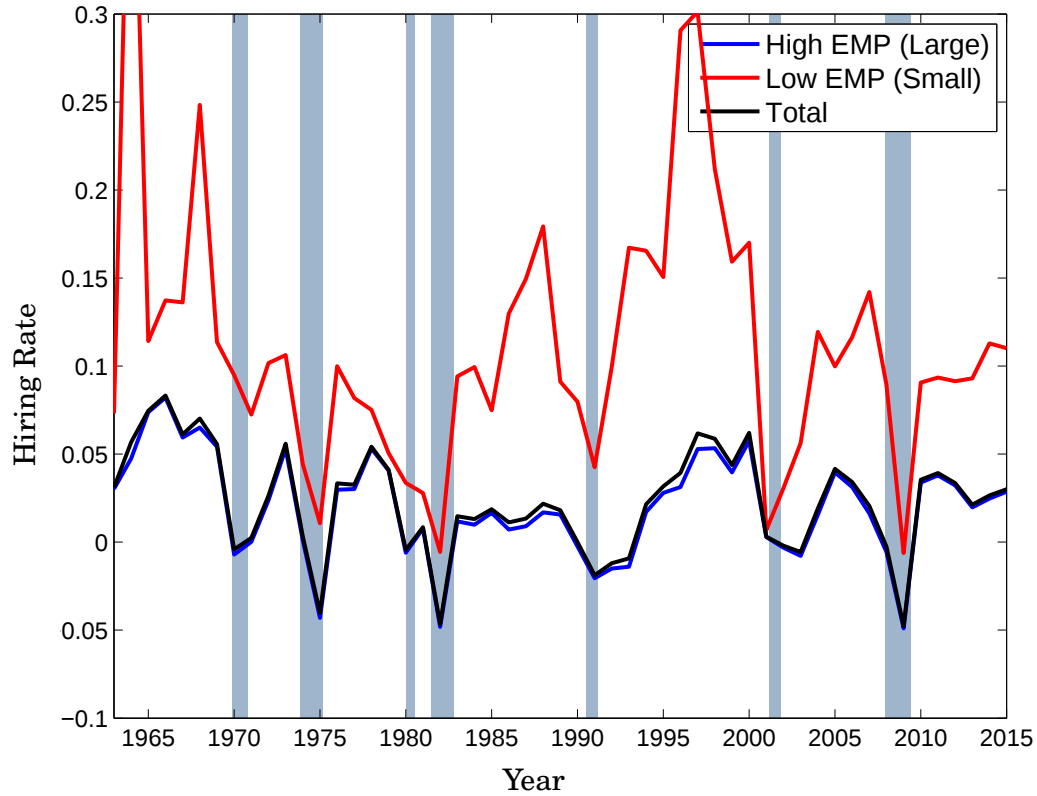


Figure 2. Hiring Rates for Subsamples of Public Firms Sorted by Number of Employees. This figure shows the hiring rates for the sample of firms in Compustat (“Total”), and of the subsamples of firms sorted on the number of employees. The “High Employment” subsample is defined by the NYSE 20% breakpoint. We include only firms with December fiscal year end to make the timing of consistent across firms. The sample period is from 1963 to 2015.

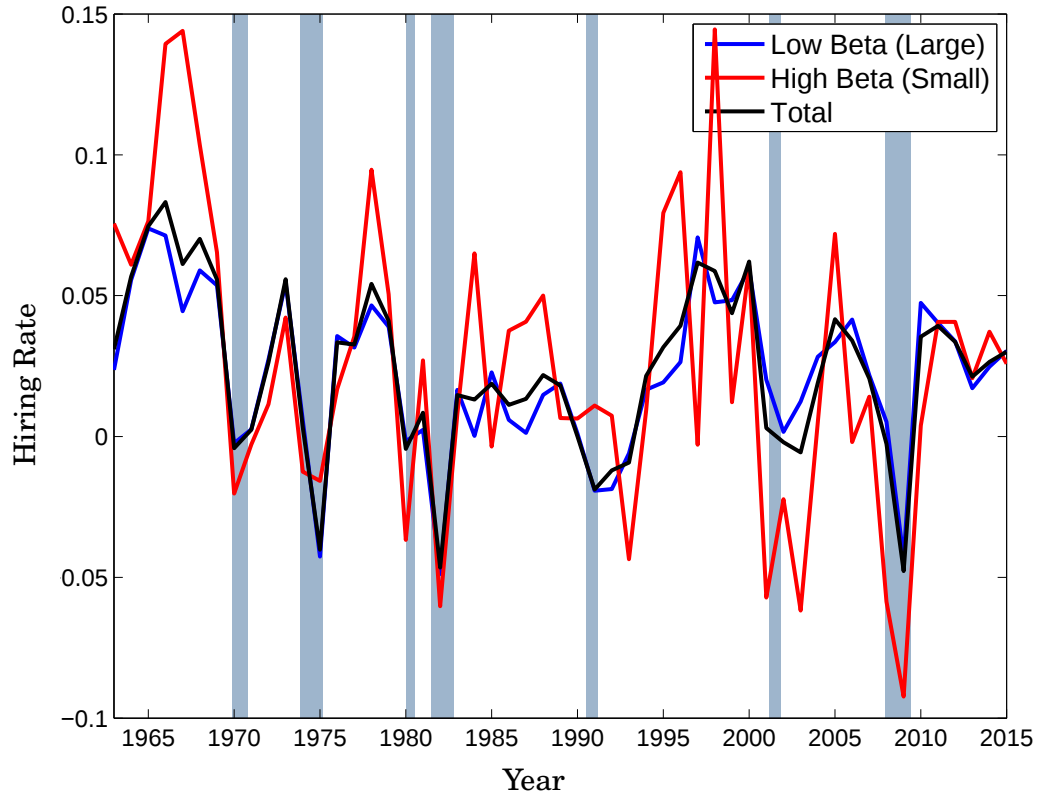


Figure 3. Hiring Rates for Subsamples of Public Firms Sorted by Conditional Market Betas. This figure shows the hiring rates for the sample of firms in Compustat (“Total”), and of the subsamples of firms sorted on the conditional market factor loadings. The “Low Beta” subsample is defined by the NYSE 20% breakpoint. We include only firms with December fiscal year end to make the timing of consistent across firms. The sample period is from 1963 to 2015.

Table IV
Summary Statistics

This table reports descriptive statistics of hiring rates. *Public* is the hiring rate calculated from Compustat all firms including all fiscal year end months. *All* is the hiring rate calculated from CES/BLS data. *Private* is hiring rate for private firms calculated from the difference between the full sample of firms and the sample of public firms. To construct size portfolios, we use *Public (Dec)*, which only includes firms with December fiscal year end. We sort portfolios either by number of employees or conditional market beta. Conditional market betas are constructed using past 12 months of returns with Dimson correction. *High (Low) Emp* stands for the hiring rate of high (low) employment portfolio. *Low (High) Beta* stands for the hiring rate of low (high) market beta portfolio. The breakpoint for High Emp and Low Beta is the first quintile of the respective variable from the sample of NYSE firms. The sample period is 1963 to 2015.

Variable	Mean	Std	AC	Correlations							
				Pub.	All	Priv.	Pub (Dec)	High Emp.	Low Emp.	Low Beta	High Beta
Public	2.90	2.82	0.52	1.00	0.78	0.41	0.98	0.97	0.58	0.94	0.77
All	1.78	2.09	0.45	0.78	1.00	0.80	0.76	0.76	0.43	0.69	0.68
Private	1.57	2.34	0.47	0.41	0.80	1.00	0.41	0.40	0.21	0.34	0.40
Public (Dec)	2.32	2.94	0.50	0.98	0.76	0.41	1.00	1.00	0.58	0.97	0.79
High Emp	2.04	2.90	0.50	0.97	0.76	0.40	1.00	1.00	0.53	0.97	0.79
Low Emp	11.31	8.15	0.34	0.58	0.43	0.21	0.58	0.53	1.00	0.54	0.46
Low Beta	2.21	2.79	0.43	0.94	0.69	0.34	0.97	0.97	0.54	1.00	0.63
High Beta	2.53	5.20	0.38	0.77	0.68	0.40	0.79	0.79	0.46	0.63	1.00

D. Empirical Specifications

We use standard short- and long-horizon predictive regressions of the form from equation 11. Both in-sample and out-of-sample tests are performed. For in-sample tests, we report regression slope coefficient, Hodrick (1992) and Newey and West (1987) p values. For out-of-sample procedure implementation, we use the first half sample as training sample. Then we implement recursive prediction as more data points become available. We report out-of-sample R^2 relative to historical mean and ENC-NEW encompassing test statistic from Clark and McCracken (2001).

III. Empirical Evidence

In this section, we document the link between hiring, aggregate discount rates and aggregate dividends in the time series. We then explain the results use the results with an investment-based asset pricing model with labor market frictions in Section I below.

A. Return and Cash Flow Predictability: Publicly-traded vs Private

Table V shows the return predictability results for hiring rates of Compustat, CES, and implied private firms. First, hiring predicts risk premium negatively. Second, public firms in Compustat are more informative about risk premium than the combination of public and private firms in CES. From three to five year horizon, Compustat hiring shows good predicting power, with in-sample R^2 from 15% to 27% and out-of-sample R^2 from 17% to 28%. CES hiring shows 11% in-sample R^2 at four year horizon, but all out-of-sample R^2 are insignificant at 10% level. As a result, the implied hiring for private firms cannot predict risk premium at any horizon. In the multivariate predicting regressions with both Compustat and CES hiring as predictors, Compustat hiring has significant coefficients at any horizon while CES coefficient is only significant at 1 year horizon with predicting sign shifting from insignificant to positively significant.

Table V
Return Predictability and Hiring Rates (Annual Frequency)

This table reports in-sample and out-of-sample R^2 for OLS predictions of aggregate risk premium (from Kenneth French's website) from 1963 to 2015 across various horizons ranging from 1 year to 5 years. Predictor variables are aggregate hiring rate from Compustat (Public Firms), CES (All Firms), and implied private firms (Private Firms) from the employment difference between CES and Compustat. Our out-of-sample procedure uses the first half of sample years as the training period and then recursively tests and retrains in subsequent periods. $p(H)$ denotes in-sample p -values constructed as in Hodrick (1992). $p(N)$ denotes in-sample p -values constructed as in Newey and West (1987). $CM Stat$ denotes the test statistics from the *New Encompassing* out-of-sample test statistic (ENC-NEW) from Clark and McCracken (2001), following the construction methodology described in Kelly and Pruitt (2013).

Hiring Rate Series	Horizon	In Sample							Out of Sample	
		R^2	Predictor (i)			Predictor (ii)			R^2	CM Stat
			Coeff	p(H)	p(N)	Coeff	p(H)	p(N)		
i) Public Firms	1	1.06	-0.59	0.516	0.516				-1.38	-0.13
	2	5.18	-1.80	0.246	0.096				5.69	0.57
	3	14.75	-3.54	0.114	0.004				17.26	1.50
	4	25.57	-5.16	0.060	0.000				27.31	2.34
	5	26.62	-5.81	0.062	0.000				27.64	2.29
i) All Firms	1	0.07	0.20	0.854	0.854				-16.99	-1.30
	2	0.30	-0.59	0.701	0.641				-8.01	-0.46
	3	5.03	-2.79	0.185	0.087				3.36	0.22
	4	10.57	-4.48	0.093	0.020				9.59	0.58
	5	9.98	-4.81	0.109	0.025				7.89	0.43
i) Private Firms	1	0.18	-0.22	0.723	0.723				-3.61	-0.39
	2	0.09	-0.22	0.834	0.799				-3.42	-0.24
	3	0.11	-0.28	0.820	0.820				-6.95	-0.25
	4	0.66	-0.78	0.580	0.656				-10.83	-0.33
	5	1.70	-1.39	0.362	0.496				-6.74	-0.21
i) Public Firms	1	3.81	-2.38	0.049	0.049	2.74	0.040	0.040	-6.92	0.94
ii) All Firms	2	7.73	-4.01	0.081	0.018	3.70	0.140	0.112	-0.68	1.04
	3	15.13	-5.22	0.128	0.008	2.79	0.471	0.353	11.21	1.54
	4	24.93	-6.57	0.126	0.006	2.57	0.602	0.497	16.15	1.92
	5	22.96	-7.01	0.174	0.016	2.72	0.638	0.537	11.31	1.70

Chen and Zhang (2011) use quarterly CES data and find that employment growth has mild predictability for risk premium. To avoid that the good results of Compustat come from data frequency issue, we construct an annual Compustat hiring rate at quarterly frequency. For each quarter, we use a subset of Compustat firms whose fiscal year end months fall in that quarter. We also construct the CES analog, annual hiring rate at quarterly frequency using quarter-to-quarter employment.

Table VI shows the return predictability results using Compustat and CES hiring rate at quarterly frequency ranging from 1 quarter horizon to 40 quarters. The in-sample and out-of-sample R^2 for both Compustat and CES first increase and then decrease with the maximum R^2 achieved at 20 quarter. Although there is not big difference between the performance of Compustat vs CES at short horizons, Compustat predicts risk premium much better than CES from horizon 28 quarter and above. This indicates that Compustat contains more information for long-run discount rate movements.

Table VII shows the dividend growth predictability results. Both Compustat hiring and CES hiring predict dividend growth negatively and they perform similarly well with in-sample and out-of-sample R^2 increasing over horizons. Hiring of private firms do not predict dividend growth. In multivariate predictive regressions with both Compustat hiring and CES hiring as predictors, both become insignificant due to their high correlation.

Table VI
Return Predictability and Hiring Rates (Quarterly Frequency)

We report in-sample and out-of-sample R^2 for OLS predictions of aggregate risk premium (from Kenneth French's website) from 1963Q1 to 2015Q4 across various horizons ranging from 1 to 40 quarters. Predictor variables are annual hiring rates for Compustat (Public Firms) and CES (All Firms) constructed at quarterly frequency using quarter-to-quarter calculation. Our out-of-sample procedure uses the first half of sample years as the training period and then recursively tests and retrains in subsequent periods. $p(H)$ denotes in-sample p -values constructed as in Hodrick (1992). $p(N)$ denotes in-sample p -values constructed as in Newey and West (1987). $CM Stat$ denotes the test statistics from the *New Encompassing* out-of-sample test statistic (ENC-NEW) from Clark and McCracken (2001), following the construction methodology described in Kelly and Pruitt (2013).

Hiring Rate Series	Horizon	In Sample				Out of Sample	
		R^2	Coeff	p(H)	p(N)	R^2	CM Stat
Public Firms	1	0.29	-0.19	0.213	0.213	-1.25	-0.156
	2	0.40	-0.31	0.247	0.189	-0.30	0.122
	4	2.07	-0.73	0.142	0.077	2.33	0.638
	8	2.98	-1.18	0.165	0.015	4.71	0.508
	12	6.78	-2.00	0.075	0.001	8.27	0.660
	16	14.15	-3.15	0.021	0.000	14.84	1.069
	20	18.33	-3.96	0.015	0.000	17.60	1.168
	24	14.88	-3.81	0.057	0.002	13.53	0.631
	28	12.53	-3.64	0.119	0.014	9.65	0.350
	32	17.40	-4.50	0.044	0.001	14.58	0.475
	36	16.68	-4.88	0.054	0.000	13.33	0.389
	40	17.72	-5.39	0.052	0.000	13.14	0.324
All Firms	1	0.43	-0.40	0.180	0.180	-1.72	-0.246
	2	1.08	-0.78	0.187	0.139	-2.30	-0.139
	4	1.59	-1.25	0.263	0.130	0.54	0.308
	8	1.36	-1.63	0.408	0.161	1.45	0.140
	12	3.54	-2.81	0.255	0.049	3.33	0.236
	16	10.11	-5.04	0.060	0.002	10.09	0.683
	20	13.70	-6.47	0.011	0.001	13.36	0.828
	24	10.10	-6.03	0.037	0.005	9.44	0.430
	28	3.73	-4.33	0.256	0.133	2.40	0.103
	32	5.94	-5.70	0.048	0.100	6.61	0.205
	36	5.49	-6.09	0.060	0.077	5.87	0.163
	40	4.00	-5.65	0.109	0.083	2.34	0.057

Table VII
Dividend Growth Predictability and Hiring Rates

This table reports in-sample and out-of-sample R^2 for OLS predictions of aggregate dividend growth (from Robert Shiller's website) from 1963 to 2015 across various horizons ranging from 1 year to 5 years. Predictor variables are aggregate hiring rate from Compustat (Public Firms), CES (All Firms), and implied private firms (Private Firms) from the employment difference between CES and Compustat. Our out-of-sample procedure uses the first half of sample years as the training period and then recursively tests and retrains in subsequent periods. $p(H)$ denotes in-sample p -values constructed as in Hodrick (1992). $p(N)$ denotes in-sample p -values constructed as in Newey and West (1987). $CM Stat$ denotes the test statistics from the *New Encompassing* out-of-sample test statistic (ENC-NEW) from Clark and McCracken (2001), following the construction methodology described in Kelly and Pruitt (2013).

Hiring Rate Series	Horizon	In Sample							Out of Sample	
		R^2	Predictor (i)			Predictor (ii)			R^2	CM Stat
			Coeff	p(H)	p(N)	Coeff	p(H)	p(N)		
i) Public Firms	1	0.15	-0.08	0.681	0.681				-1.05	-0.11
	2	5.47	-0.85	0.021	0.017				2.25	0.36
	3	12.71	-1.67	0.002	0.001				10.23	1.00
	4	19.01	-2.30	0.000	0.000				17.45	1.62
	5	26.05	-2.76	0.000	0.000				23.38	2.23
i) All Firms	1	0.26	0.14	0.692	0.692				-2.31	-0.26
	2	3.10	-0.87	0.200	0.148				-0.93	0.07
	3	10.53	-2.05	0.038	0.005				8.47	0.83
	4	18.09	-3.03	0.008	0.004				17.20	1.57
	5	27.66	-3.84	0.000	0.007				27.77	2.79
i) Private Firms	1	2.48	0.39	0.237	0.237				-2.43	-0.02
	2	0.17	-0.18	0.757	0.758				-4.70	-0.30
	3	2.78	-0.94	0.280	0.289				-2.86	-0.14
	4	5.76	-1.53	0.116	0.252				-4.93	-0.22
	5	7.62	-1.80	0.023	0.290				-8.80	-0.39
i) Public Firms	1	-2.17	-0.42	0.292	0.292	0.58	0.390	0.390	-3.55	-0.26
ii) All Firms	2	1.55	-0.91	0.175	0.223	0.09	0.938	0.936	-3.53	-0.02
	3	9.52	-1.24	0.230	0.194	-0.73	0.687	0.599	4.28	0.66
	4	17.34	-1.40	0.294	0.260	-1.54	0.491	0.429	4.04	0.80
	5	26.99	-1.37	0.350	0.347	-2.39	0.271	0.346	-1.01	0.76

B. Return and Cash Flow Predictability: Compustat Size Portfolios

In order to show how size affects risk premium and dividend growth predictability, we sort portfolios based on either EMP or market beta (calculated with past 12 months data and Dimson correction). Table VIII shows the results for return predictions across size portfolios. First, the return predictability of Compustat hiring rate comes mainly from large firms, i.e., high EMP firms and low beta firms. For example, all public firms with December sample has in-sample R^2 of 23.36% and out-of-sample R^2 of 25.09% at 4 year horizon. For High EMP (low beta) firms, the corresponding R^2 are 22.8% (27.43%) and 24.40% (30.16%), while they are for 7.10% (14.18%) and 4.44% (14.85%) for low EMP (high beta) firms. Second, the predictive coefficients are much more negative for large firms than small firms. Take 4 year horizon for an example, the coefficient is -4.74 (-5.35) for high EMP (low beta) firms, while it is -0.94 (-2.06) for low EMP (high beta) firms.

Table IX shows the results for dividend growth predictability across size portfolios. For EMP sorted portfolios, high EMP firms capture more of the predicting power than low EMP firms. At five year horizon, the R^2 achieves 22.28% in sample and 20.13% for high EMP firms, while low EMP firms only generate 10.18% and 9.31%. For market beta sorted portfolios, high beta firms actually predict dividend growth better. At five year horizon, high beta firms produce R^2 of 29.67% in sample and 31.35% out of sample, while they are 14.49% and 10.17% for low beta firms. Although the two sorting methods generate different pattern of dividend predictability for our notion of small and large firms, the two sorting do produce a set of different firms besides the majority of same firms.

C. Is The Predictability Coming Directly from Hiring Rate or through its Relation to Cash Flow Growth?

Since Compustat hiring shows both return and dividend growth predictability, a natural question to ask is, does return predictability come from dividend growth pre-

dictability? Table X addresses this concern. We use sales for the proxy of cash flow news. We use the residuals of regressing hiring rates on sales growths to predict risk premium in Panel A. Clearly, the residuals still predict risk premium fairly well. At 4 year horizon, all public firms produce in sample R^2 of 11.70% and out of sample R^2 of 10.79%. For size portfolios, residuals of large firms predict better than that of small firms. Large firms, i.e., high EMP (after controlling both high EMP and low EMP sales growth) or low beta (after controlling both low beta and high beta sales growth) firms, have predicting in-sample R^2 of 11.39% and 12.09% and out-of-sample R^2 of 10.23% and 10.45%. But controlling hiring rates, sales growth shows no predictability for risk premium as shown in Panel B. Most in-sample R^2 are small and insignificant. But sales growth not explained by hiring rates has some predictability at one-year short horizon. The out-of-sample R^2 is 8.48% for all public firms and 9.71% for high EMP firms and 10.22% for low beta firms.

Table VIII
Return Predictability
Hiring Rates of Subsamples by Firms Sorted on Size and Market Risk
Loadings

We report in-sample and out-of-sample R^2 for OLS predictions of aggregate risk premium (from Kenneth French's website) from 1963 to 2015 across various horizons ranging from 1 to 5 years. Predictor variables are annual hiring rates for Compustat (Public Firms (Dec), only firms with December fiscal year end) and size portfolios sorted on EMP or market beta (which is calculated using past 12 months with Dimson correction). *High (Low) Emp* stands for the hiring rate of high (low) employment portfolio. *Low (High) Beta* stands for the hiring rate of low (high) market beta portfolio. The breakpoint for High Emp and Low Beta is the first quintile of the respective variable from the sample of NYSE firms. Our out-of-sample procedure uses the first half of sample years as the training period and then recursively tests and retrain in subsequent periods. $p(H)$ denotes in-sample p -values constructed as in Hodrick (1992). $p(N)$ denotes in-sample p -values constructed as in Newey and West (1987). *CM Stat* denotes the test statistics from the *New Encompassing* out-of-sample test statistic (ENC-NEW) from Clark and McCracken (2001), following the construction methodology described in Kelly and Pruitt (2013).

Hiring Rate Series	Horizon	In Sample				Out of Sample	
		R^2	Coeff	$p(H)$	$p(N)$	R^2	CM Stat
All Public Firms (December Sample)	1	0.46	-0.37	0.652	0.652	-2.95	-0.32
	2	3.24	-1.37	0.334	0.172	2.67	0.27
	3	11.44	-2.99	0.151	0.012	13.27	1.08
	4	23.36	-4.73	0.072	0.000	25.09	2.02
	5	27.14	-5.65	0.066	0.000	28.67	2.29
High Emp. Firms	1	0.36	-0.33	0.686	0.686	-3.58	-0.40
	2	3.30	-1.40	0.326	0.171	2.90	0.30
	3	11.49	-3.04	0.151	0.013	13.33	1.09
	4	22.80	-4.74	0.078	0.000	24.40	1.95
	5	25.76	-5.59	0.075	0.000	27.26	2.11
Low Emp. Firms	1	0.95	-0.19	0.482	0.482	-1.40	-0.15
	2	0.17	-0.11	0.800	0.715	-2.28	-0.15
	3	1.28	-0.36	0.555	0.409	-1.66	-0.09
	4	7.10	-0.94	0.235	0.076	4.44	0.27
	5	17.57	-1.63	0.123	0.000	9.03	0.74
Low Beta Firms	1	0.81	-0.52	0.555	0.555	-2.02	-0.19
	2	2.93	-1.37	0.333	0.197	1.70	0.20
	3	11.04	-3.08	0.127	0.015	12.80	1.04
	4	27.43	-5.35	0.039	0.000	30.16	2.76
	5	31.26	-6.38	0.041	0.000	35.08	2.96
High Beta Firms	1	0.04	0.06	0.882	0.882	-5.76	-0.49
	2	3.26	-0.78	0.371	0.198	2.32	0.27
	3	10.05	-1.58	0.205	0.012	11.63	0.99
	4	14.18	-2.06	0.164	0.002	14.85	1.11
	5	16.21	-2.44	0.143	0.004	12.72	1.05

Table IX
Dividend Growth Predictability
Hiring Rates of Subsamples by Firms Sorted on Size and Betas

We report in-sample and out-of-sample R^2 for OLS predictions of aggregate dividend growth (from Robert Shiller's website) from 1963 to 2015 across various horizons ranging from 1 to 5 years. Predictor variables are annual hiring rates for Compustat (Public Firms (Dec), only firms with December fiscal year end) and size portfolios sorted on EMP or market beta (which is calculated using past 12 months with Dimson correction). *High (Low) Emp* stands for the hiring rate of high (low) employment portfolio. *Low (High) Beta* stands for the hiring rate of low (high) market beta portfolio. The breakpoint for High Emp and Low Beta is the first quintile of the respective variable from the sample of NYSE firms. Our out-of-sample procedure uses the first half of sample years as the training period and then recursively tests and retrains in subsequent periods. $p(H)$ denotes in-sample p -values constructed as in Hodrick (1992). $p(N)$ denotes in-sample p -values constructed as in Newey and West (1987). *CM Stat* denotes the test statistics from the *New Encompassing* out-of-sample test statistic (ENC-NEW) from Clark and McCracken (2001), following the construction methodology described in Kelly and Pruitt (2013).

Hiring Rate Series	Horizon	In Sample				Out of Sample	
		R^2	Coeff	p(H)	p(N)	R^2	CM Stat
All Public Firms (December Sample)	1	0.01	-0.02	0.905	0.905	-1.26	-0.10
	2	5.43	-0.77	0.031	0.029	1.78	0.46
	3	12.09	-1.49	0.002	0.002	9.02	1.07
	4	17.43	-2.01	0.000	0.000	14.89	1.66
	5	27.63	-2.61	0.000	0.000	25.56	2.82
High Emp. Firms	1	0.66	0.16	0.479	0.479	-0.62	-0.07
	2	1.47	-0.43	0.272	0.291	-2.98	-0.07
	3	6.66	-1.18	0.021	0.023	2.68	0.41
	4	13.32	-1.87	0.002	0.002	10.65	1.04
	5	22.28	-2.50	0.000	0.000	20.13	1.96
Low Emp. Firms	1	0.74	0.06	0.246	0.246	-1.99	-0.05
	2	0.50	-0.09	0.372	0.512	-1.00	-0.04
	3	3.77	-0.31	0.054	0.153	2.25	0.15
	4	6.70	-0.47	0.019	0.095	5.51	0.35
	5	10.18	-0.60	0.006	0.043	9.31	0.62
Low Beta Firms	1	0.82	0.19	0.381	0.381	-0.15	-0.01
	2	0.95	-0.36	0.325	0.386	-3.81	-0.14
	3	4.61	-1.02	0.030	0.063	0.04	0.22
	4	8.28	-1.53	0.005	0.013	4.49	0.53
	5	14.49	-2.09	0.001	0.001	10.17	0.99
High Beta Firms	1	1.19	0.12	0.465	0.465	-1.55	-0.17
	2	0.87	-0.18	0.477	0.470	-1.74	-0.06
	3	5.95	-0.62	0.109	0.040	3.81	0.43
	4	17.37	-1.19	0.007	0.000	17.21	1.78
	5	29.67	-1.60	0.000	0.000	31.50	3.99

Table X
Return Predictability: Hiring Rates or Cash Flow Growth?

We report in-sample and out-of-sample R^2 for OLS predictions of aggregate risk premium (from Kenneth French's website) from 1963 to 2015 across various horizons ranging from 1 to 5 years. Predictor variables are residuals of annual hiring rates (HN) or sales growth rates (SA) for Compustat size portfolios sorted on EMP or market beta. Our out-of-sample procedure uses the first half of sample years as the training period and then recursively tests and retrains in subsequent periods. $p(H)$ denotes in-sample p -values constructed as in Hodrick (1992). $p(N)$ denotes in-sample p -values constructed as in Newey and West (1987). *CM Stat* denotes the test statistics from the *New Encompassing* out-of-sample test statistic (ENC-NEW) from Clark and McCracken (2001), following the construction methodology described in Kelly and Pruitt (2013).

Panel A: Component of Hiring Rate Not Explained by Sales Growth Rates							
Hiring Rate	Horizon	In Sample				Out of Sample	
Residual From		R^2	Coeff	p(H)	p(N)	R^2	CM Stat
<i>Predictor: Hiring Rate Not Explained by Sales Growth of All Public Firms</i>							
All Public Firms (December Sample)	1	0.18	0.28	0.762	0.762	-1.71	-0.18
	2	0.47	-0.63	0.732	0.602	-1.03	-0.07
	3	4.32	-2.22	0.418	0.167	3.73	0.27
	4	11.70	-4.10	0.242	0.026	10.79	0.71
	5	17.25	-5.52	0.183	0.010	15.64	1.02
<i>Predictor: Hiring Rate Not Explained by Sales Growth Series of Emp Sorted Firms</i>							
High Emp. Firms	1	0.27	0.35	0.699	0.699	-1.82	-0.20
	2	0.61	-0.73	0.688	0.551	-0.44	-0.02
	3	4.69	-2.38	0.392	0.145	4.27	0.32
	4	11.39	-4.15	0.246	0.029	10.23	0.68
	5	16.05	-5.46	0.197	0.014	14.54	0.94
Low Emp. Firms	1	0.42	-0.14	0.591	0.591	-1.24	-0.14
	2	0.02	-0.04	0.932	0.869	-0.61	-0.05
	3	0.54	-0.26	0.693	0.478	0.06	0.01
	4	4.30	-0.82	0.336	0.125	3.17	0.18
	5	14.57	-1.66	0.171	0.000	6.81	0.45
<i>Predictor: Hiring Rate Not Explained by Sales Growth Series of Beta Sorted Firms</i>							
High Beta Firms	1	0.11	0.24	0.789	0.789	-1.87	-0.21
	2	0.02	0.13	0.933	0.912	-3.36	-0.24
	3	2.50	-1.87	0.424	0.240	0.87	0.14
	4	12.09	-4.61	0.150	0.031	10.45	0.89
	5	13.74	-5.43	0.135	0.022	13.39	1.02
Low Beta Firms	1	0.05	-0.16	0.864	0.864	-2.05	-0.25
	2	0.00	0.01	0.994	0.992	-3.02	-0.21
	3	1.14	-1.24	0.595	0.429	-0.42	0.01
	4	2.83	-2.16	0.454	0.230	1.42	0.13
	5	5.21	-3.23	0.359	0.115	1.18	0.22

Table X
Return Predictability: Hiring Rates or Cash Flow Growth? (Cont'd)

Panel B: Component of Sales Growth Rate Not Explained by Hiring Rates							
Sales Growth	Horizon	In Sample				Out of Sample	
Residual		R^2	Coeff	p(H)	p(N)	R^2	CM Stat
<i>Predictor: Sales Growth Not Explained by Hiring Rate of All Public Firms</i>							
All Public Firms (December Sample)	1	4.24	-0.69	0.120	0.120	8.48	1.48
	2	3.24	-0.85	0.313	0.076	4.14	0.40
	3	3.39	-1.02	0.392	0.065	2.76	0.19
	4	3.35	-1.16	0.428	0.185	-0.98	-0.04
	5	0.99	-0.70	0.673	0.510	-7.35	-0.27
<i>Predictor: Sales Growth Not Explained by Hiring Rates of Emp Sorted Firms</i>							
High Emp. Firms	1	4.87	-0.74	0.084	0.084	9.71	1.77
	2	2.92	-0.81	0.312	0.095	3.50	0.34
	3	3.06	-0.98	0.382	0.085	2.15	0.14
	4	3.69	-1.22	0.365	0.153	-0.07	0.00
	5	1.85	-0.96	0.516	0.328	-3.70	-0.14
Low Emp. Firms	1	1.42	-0.34	0.322	0.322	0.01	0.03
	2	0.73	-0.33	0.556	0.498	-2.99	-0.19
	3	0.65	-0.37	0.640	0.548	-4.39	-0.19
	4	0.76	-0.44	0.648	0.574	-6.54	-0.23
	5	0.00	-0.02	0.989	0.986	-9.69	-0.25
<i>Predictor: Sales Growth Not Explained by Hiring Rates of Beta Sorted Firms</i>							
Low Beta Firms	1	4.94	-0.68	0.094	0.094	10.22	1.81
	2	2.52	-0.67	0.377	0.115	2.80	0.26
	3	2.28	-0.75	0.478	0.123	0.68	0.06
	4	1.66	-0.74	0.575	0.343	-3.68	-0.16
	5	0.26	-0.33	0.822	0.706	-7.12	-0.26
High Beta Firms	1	1.94	-0.56	0.266	0.266	2.09	0.38
	2	3.77	-1.10	0.254	0.043	4.53	0.47
	3	3.81	-1.31	0.351	0.066	3.32	0.21
	4	4.49	-1.59	0.334	0.132	1.53	0.08
	5	1.77	-1.10	0.562	0.438	-7.56	-0.27

Table XI reports the dividend growth predictability to further verify that sales growth captures mainly cash flow news and that hiring rate captures news about both discount rates and cash flows. As shown in Panel A, for all public firms (December sample) and EMP sorted portfolios, hiring rate not explained by sales growth has mild predictability for dividend growth, but no predictability for beta sorted portfolios. As shown in Panel B, sales growth rates not explained hiring rate show moderate predictability for all public firms (December sample), EMP portfolios, and market beta portfolios. In short, controlling cash flow news, hiring rate still predicts risk premium. Hiring rate does include some cash flow news, but also discount rate news.

Table XI
Dividend Growth Predictability: Hiring Rates or Cash Flow Growth?

We report in-sample and out-of-sample R^2 for OLS predictions of aggregate risk premium (from Kenneth French's website) from 1963 to 2015 across various horizons ranging from 1 to 5 years. Predictor variables are residuals of annual hiring rates (HN) or sales growth rates (SA) for Compustat size portfolios sorted on EMP or market beta. Our out-of-sample procedure uses the first half of sample years as the training period and then recursively tests and retrain in subsequent periods. $p(H)$ denotes in-sample p -values constructed as in Hodrick (1992). $p(N)$ denotes in-sample p -values constructed as in Newey and West (1987). $CM Stat$ denotes the test statistics from the *New Encompassing* out-of-sample test statistic (ENC-NEW) from Clark and McCracken (2001), following the construction methodology described in Kelly and Pruitt (2013).

Panel A: Component of Hiring Rate Not Explained by Sales Growth Rates							
Hiring Rate	Horizon	In Sample				Out of Sample	
Residual		R^2	Coeff	p(H)	p(N)	R^2	CM Stat
<i>Predictor: Hiring Rate Not Explained by Sales Growth of All Public Firms</i>							
All Public Firms (December Sample)	1	2.54	0.38	0.144	0.144	2.34	0.33
	2	0.02	-0.05	0.906	0.916	-2.15	-0.14
	3	1.98	-0.77	0.215	0.277	-0.91	0.01
	4	5.82	-1.49	0.045	0.058	3.92	0.31
	5	9.05	-1.92	0.022	0.031	6.33	0.50
<i>Predictor: Hiring Rate Not Explained by Sales Growth Series of Emp Sorted Firms</i>							
High Emp. Firms	1	2.27	0.37	0.192	0.192	2.03	0.28
	2	0.02	-0.06	0.902	0.913	-2.86	-0.18
	3	1.71	-0.73	0.237	0.320	-1.90	-0.05
	4	4.95	-1.41	0.050	0.080	2.41	0.21
	5	8.09	-1.86	0.025	0.037	5.02	0.42
Low Emp. Firms	1	0.57	0.06	0.381	0.381	-1.66	-0.15
	2	0.31	-0.08	0.388	0.618	-0.58	-0.04
	3	2.18	-0.27	0.064	0.259	1.63	0.10
	4	2.92	-0.35	0.052	0.209	2.54	0.15
	5	4.61	-0.45	0.031	0.100	4.56	0.28
<i>Predictor: Hiring Rate Not Explained by Sales Growth Series of Beta Sorted Firms</i>							
Low Beta Firms	1	0.65	0.21	0.407	0.407	-0.46	-0.05
	2	0.03	-0.08	0.857	0.877	-6.08	-0.30
	3	0.36	-0.36	0.583	0.633	-7.79	-0.24
	4	0.93	-0.66	0.424	0.455	-8.63	-0.21
	5	1.17	-0.76	0.447	0.474	-12.85	-0.26
High Beta Firms	1	0.62	0.20	0.430	0.430	-0.56	-0.05
	2	0.15	-0.17	0.687	0.730	-1.34	-0.09
	3	1.15	-0.63	0.289	0.355	-0.43	0.01
	4	1.12	-0.70	0.339	0.437	-1.29	-0.03
	5	0.59	-0.52	0.480	0.626	-2.45	-0.07

IV. Conclusion

Firm's hiring decisions vary with changes in aggregate discount rates and expected cash flows (dividends). We report three major findings. First, using short- and long-horizon predictability regressions, we show that the hiring rate of publicly traded firms, but not of private firms, negatively predicts aggregate stock market returns (discount rates) in the U.S. economy for the period between 1963 and 2015. The lack of return predictability of the hiring rate of private firms helps us understand why the predictability of the hiring rate of the whole economy (which includes both private and publicly traded firms) is weak, as reported in previous studies (Chen and Zhang, 2010). Second, we show that the link between hiring rate and future returns is significantly stronger in large firms than in small firms. Because private firms tend to be smaller than publicly traded firms, this finding helps us understand why the hiring rate of the private firms is a weak predictor of returns. Third, we show that hiring predicts aggregate dividends with a negative sign. Theoretically, we show that the results are in line with the predictions from a standard neoclassical model with labor adjustment costs.

Table XI
Dividend Growth Predictability: Hiring Rates or Cash Flow Growth?
(Cont'd)

Panel B: Component of Sales Growth Rate Not Explained by Hiring Rates							
Sales Growth	Horizon	In Sample				Out of Sample	
Residual		R^2	Coeff	p(H)	p(N)	R^2	CM Stat
<i>Predictor: Sales Growth Not Explained by Hiring Rate of All Public Firms</i>							
All Public Firms (December Sample)	1	3.25	-0.22	0.072	0.072	0.28	0.20
	2	3.92	-0.43	0.049	0.059	1.94	0.20
	3	3.65	-0.54	0.081	0.112	2.76	0.19
	4	3.48	-0.61	0.102	0.149	2.48	0.15
	5	6.56	-0.86	0.013	0.104	4.76	0.30
<i>Predictor: Sales Growth Not Explained by Hiring Rates of Emp. Sorted Firms</i>							
High Emp. Firms	1	3.19	-0.22	0.086	0.086	0.93	0.23
	2	4.29	-0.45	0.047	0.058	2.48	0.23
	3	4.33	-0.59	0.066	0.104	2.99	0.20
	4	4.10	-0.67	0.090	0.147	2.67	0.16
	5	7.54	-0.93	0.010	0.102	5.48	0.35
Low Emp. Firms	1	0.36	-0.06	0.604	0.604	-0.79	-0.07
	2	0.55	-0.13	0.411	0.518	-1.42	-0.10
	3	1.09	-0.24	0.292	0.415	-1.32	-0.07
	4	2.61	-0.42	0.082	0.223	0.68	0.04
	5	3.87	-0.53	0.046	0.240	0.64	0.05
<i>Predictor: Sales Growth Not Explained by Hiring Rates of Beta Sorted Firms</i>							
Low Beta Firms	1	4.65	-0.24	0.013	0.013	2.45	0.53
	2	5.33	-0.45	0.015	0.024	3.52	0.34
	3	4.81	-0.55	0.028	0.072	3.58	0.25
	4	3.53	-0.56	0.078	0.150	1.88	0.12
	5	5.41	-0.71	0.023	0.125	3.21	0.20
High Beta Firms	1	1.90	-0.20	0.270	0.270	-2.71	-0.21
	2	2.76	-0.43	0.171	0.130	0.01	0.05
	3	3.25	-0.62	0.179	0.097	1.96	0.15
	4	4.82	-0.85	0.116	0.078	3.78	0.25
	5	10.86	-1.31	0.003	0.042	9.57	0.66

REFERENCES

- Belo, Frederico, Xiaoji Lin, and Santiago Bazdresch, 2014, Labor hiring, investment and stock return predictability in the cross section, *Journal of Political Economy* 122, 129–177.
- Belo, Frederico, Xiaoji Lin, Jun Li, and Xiaofei Zhao, 2015, Labor-Force Heterogeneity and Asset Prices: The Importance of Skilled Labor, working paper.
- Berk, Jonathan B., Richard C. Green, and Vasant Naik, 1999, Optimal investment, growth options, and security returns, *Journal of Finance* 54, 1553–1607.
- Bloom, Nicholas, 2009, The impact of uncertainty shocks, *Econometrica* 77, 623–685.
- Boyd, John H., Jian Hu, and Ravi Jagannathan, 2005, The stock market’s reaction to unemployment news: Why bad news is usually good for stocks, *Journal of Finance* 60, 649–672.
- Campbell, John Y., 1996, Understanding Risk and Return, *Journal of Political Economy* 104, 298–345.
- Campbell, John Y., and John H. Cochrane, 1999, By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior, *Journal of Political Economy* 107.
- Campbell, John Y., and Robert J. Shiller, 1988, The dividend-price ratio and expectations of future dividends and discount factors, *Review of financial studies* 1, 195–228.
- Carlson, Murray, Adlai Fisher, and Ron Giammarino, 2004, Corporate investment and asset price dynamics: Implications for the cross-section of returns, *Journal of Finance* 59, 2577–2603.
- Chen, L., and L. Zhang, 2011, Do time-varying risk premiums explain labor market performance?, *Journal of Financial Economics* 99, 385–399.
- Clark, Todd, and Michael McCracken, 2001, Tests of equal forecast accuracy and encompassing for nested models, *Journal of Econometrics* 105, 85–110.
- Cochrane, John H., 2008, The Dog That Did Not Bark: A Defense of Return Predictability, *Review of Financial Studies* 21, 1533–1575.
- Danthine, Jean-Pierre, and John B. Donaldson, 2002, Labor relations and asset returns, *Review of Economic Studies* 69, 41–64.

- Davis, Steven J., R. Jason Faberman, and John Haltiwanger, 2006, The flow approach to labor markets: new data sources and micro-macro links, *Journal of Economic Perspectives* 20, 3–26.
- Donangelo, Andres, 2014, Labor mobility: Implications for asset pricing, *Journal of Finance* 68, 1321–1346.
- Donangelo, Andres, Esther Eiling, and Miguel Palacios, 2010, Aggregate asset-pricing implications of human capital mobility in general equilibrium.
- Donangelo, Andres, Francois Gourio, and Miguel Palacios, 2016, The Cross-Section of Labor Leverage and Equity Returns, working paper.
- Eisfeldt, Andrea L., and Dimitris Papanikolaou, 2013, Organization Capital and the Cross-Section of Expected Returns, *Journal of Finance* 68, 1365–1406.
- Fama, Eugene F., and Kenneth R. French, 1988, Dividend yields and expected stock returns, *Journal of Financial Economics* 22, 3–25.
- Fama, Eugene F., and Kenneth R. French, 1989, Business conditions and expected returns on stocks and bonds, *Journal of Financial Economics* 25, 23–49.
- Fama, Eugene F., and Kenneth R. French, 2008, Dissecting anomalies, *Journal of Finance* 63, 1653–1678.
- Fama, Eugene F., and G. William Schwert, 1977, Human Capital and Capital Market Equilibrium, *Journal of Financial Economics* 4, 95–125.
- Favilukis, Jack, and Xiaoji Lin, 2016, Wage Rigidity: A Solution to Several Asset Pricing Puzzles, *Review of Financial Studies* 29, 148–192.
- Gourio, François, 2007, Labor leverage, firms’ heterogeneous sensitivities to the business cycle, and the Cross-Section of expected returns, *working paper* .
- Harvey, Campbell R., Yan Liu, and Heqing Zhu, 2014, ... And the cross-section of expected returns, working paper.
- Hodrick, Robert J., 1992, Dividend yields and expected stock returns: Alternative procedures for inference and measurement, *Review of Financial studies* 5, 357–386.
- Imrohoroglu, Ayse, and Selale Tuzel, 2014, Firm-level productivity, risk, and return, *Management Science* 60, 2073–2090.
- Kelly, Bryan T., and Seth Pruitt, 2013, Market expectations in the cross-section of present values, *Journal of Finance* 68(5), 1721–1756.

- Kogan, Leonid, 2001, An equilibrium model of irreversible investment, *Journal of Financial Economics* 62, 201–245.
- Kogan, Leonid, 2004, Asset prices and real investment, *Journal of Financial Economics* 73, 411–431.
- Kogan, Leonid, and Dimitris Papanikolaou, 2013, Firm characteristics and stock returns: The role of investment-specific shocks, *Review of Financial Studies* 26, 2718–2759.
- Kogan, Leonid, and Dimitris Papanikolaou, 2014, Growth opportunities, technology shocks, and asset prices, *Journal of Finance* 69, 675–718.
- Kuehn, Lars-Alexander, Mikhail Simutin, and Jessie Jiaxu Wang, 2016, Labor capital asset pricing model, *Journal of Finance* forthcoming.
- Lettau, Martin, and Sydney Ludvigson, 2002, Time-varying risk premia and the cost of capital: An alternative implication of the Q theory of investment, *Journal of Monetary Economics* 49, 31–66.
- Lettau, Martin, Sydney C. Ludvigson, and Sai Ma, 2014, Capital Share Risk and Shareholder Heterogeneity in US Stock Pricing, working paper.
- Liu, Laura Xiaolei, Toni M. Whited, and Lu Zhang, 2009, Investment-based Expected Stock Returns, *Journal of Political Economy* 117, 1105–1139.
- Livdan, Dmitry, Horacio Sapriza, and Lu Zhang, 2009, Financially Constrained Stock Returns, *Journal of Finance* 64, 1827–1862.
- Lustig, H., and S. Van Nieuwerburgh, 2008, The returns on human capital: Good news on wall street is bad news on main street, *Review of Financial Studies* 21, 2097–2137.
- Mayers, David, 1973, Nonmarketable Assets and the Determination of Capital Asset Prices in the Absence of a Riskless Asset, *Journal of Business* 46, 258–267.
- Merz, Monika, and Eran Yashiv, 2007, Labor and the Market Value of the Firm, *American Economic Review* 97, 1419–1431.
- Newey, Whitney K., and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.
- Ochoa, Marcelo, 2013, Volatility, labor heterogeneity and asset prices, working paper.

- Palacios, Miguel, 2015, Human Capital as an Asset Class Implications From a General Equilibrium Model, *Review of Financial Studies* 28, 978–1023.
- Parlour, Christine, and Johan Walden, 2011, General Equilibrium Returns to Human and Investment Capital under Moral Hazard, *Review of Economic Studies* 78, 394–428.
- Petrosky-Nadeau, Nicolas, Lu Zhang, and Lars-Alexander Kuehn, 2013, An equilibrium asset pricing model with labor market search, working paper.
- Santos, Tano, and Pietro Veronesi, 2006, Labor Income and Predictable Stock Returns, *Review of Financial Studies* 19, 1–44.
- Shiller, Robert J., 1981, Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends?, *American Economic Review* 71, 421–436.
- Shumway, Tyler, 1997, The Delisting Bias in CRSP Data, *Journal of Finance* 52, 327–340.
- Tuzel, Selale, 2010, Corporate Real Estate Holdings and the Cross-Section of Stock Returns, *Review of Financial Studies* 23, 2268 –2302.
- Uhlig, Harald, 2007, Explaining Asset Prices with External Habits and Wage Rigidities in a DSGE Model, *American Economic Review* 97, 239–243.
- Zhang, Lu, 2005, The value premium, *Journal of Finance* 60, 67–103.
- Zhang, Miao Ben, 2015, Labor-Technology Substitution: Implications for Asset Pricing, working paper.
- Zhang, Mindy, 2014, Who bears firm risk? implications for cash flow volatility, working paper.