Labor Hiring and Discount Rates*

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ABSTRACT

Using a standard production model with labor market frictions, we show that firms' optimal hiring is a forward looking decision that depends on aggregate discount rates and future dividends. Consistent with the model, we find empirically that: (a) the aggregate hiring rate of public listed firms negatively predicts aggregate stock market excess returns (discount rates) and aggregate cash-flows both in-sample and out-of-sample; (b) large, low market beta, and old firms explain most of the return predictability of the aggregate hiring rate for stock returns; and (c) the explanatory power of the aggregate hiring rate for returns is not explained by traditional cash-flow based measures of performance. Taken together, our results 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 against cash flow growth predictability, at least at at the aggregate level. However, baring a few exceptions that we discuss below, less attention was given to the study of the predictive power of labor market variables. In this paper, we help close this gap.

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. The presence of adjustment costs and other labor demand frictions make hiring and firing decisions forward looking and potentially informative about discount rate and *future* cash flows.[1] To establish the theoretical link between labor hiring, and stock return and dividend predictability, we consider a simplified version of the model in Belo, Lin, and Bazdresch (2014) (henceforth BLB) who consider an economy with labor market frictions. In the model, labor hiring and firing is costly for firms, which is captured through an adjustment cost function. Firms' take prices as given and choose how many workers to hire or fire to maximize the value of the firm.

In the model, the firm's first order condition for hiring expresses a relation between the firm's optimal hiring rate, the expected future firm profitability (measured by firm's dividends relative to its labor stock, and also future dividend growth), and the expected future stock return. We use this relationship to guide the empirical analysis. We use short- and long-horizon predictive regressions using the aggregate (computed across different groups of firms) hiring rate to predict aggregate stock market excess returns (discount rates) and dividends.

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

Our empirical findings can be summarized as follows. We show that the aggregate hiring rate of public firms negatively predicts aggregate stock market excess returns both in-sample and out-of-sample. For example, at the three and five year horizon, the in-sample R^2 in the predictability regression is 15% and 27%, while the out-of-sample R^2 is 17% and 28%. Interpreting this result through the lens of the model, the negative slope in the regression means that when discount rate falls, the marginal benefit of labor to firm value increases, which in turn motivates the firm to hire more workers.

The previous finding is in contrast with the empirical findings in Chen and Zhang (2011) who find little evidence that aggregate hiring of all firms in the economy (which includes both public and private firms) can predict aggregate risk premium. We show that this result is fully explained by the hiring decisions of privately held firms. Because private firms are plentiful they dominate the aggregate measures. However, we show that the aggregate hiring rate of the private firms is disconnected from the movements in the aggregate discount rate.

To help understand the previous result, we perform predictability analysis across different groups of public firms: small and large firms, low and high market beta firms, and young and old firms. We focus on these groups of firms because, as we discuss in the model, these firms should have different sensitivities to changes in the expected market excess return (aggregate discount rates), which is the variable we want to forecast. Then, to the extent that small, high market beta, young firms are representative characteristics of private firms, the results across these set of firms helps us understand the opposite evidence on the link between hiring and aggregate discount rates of public and private firms.

Consistent with the previous discussion, we find that the link between the hiring rates across these groups of firms and discount rates is very different. The hiring rate of large, low market beta, and old firms is significantly and negatively correlated with aggregate discount rates, but the hiring rate of small, high market beta and young firms, for the most part, is not. Thus, the hiring rate of large, low market beta, and old firms explains most of the return predictability of the aggregate hiring rate of public traded firms for stock returns.

Finally, we also find that the aggregate hiring rate of public firms predicts aggregate dividends with a negative sign. Because the hiring of publicly traded firms shows both return and dividend growth predictability, a natural question to ask is, does return predictability come form dividend growth predictability? Our analysis suggests that this is not the case. Using sales growth as a proxy for cash flow news, we show that the residuals of regressing hiring rates on aggregate sales growth still predict aggregate stock market excess returns both in-sample and out-of-sample. Taken together, our results demonstrate the significance of labor hiring to understand the dynamic nature of discount rates and cash flows.

Related Literature

Our work contributes to our understanding about the relationship between labor income and asset returns. This literature go 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 focus 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 re-

[2]More 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).

turns, 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 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 1 presents a simple neoclassical production model to guide the empirical analysis. Section 2 describes the financial and labor market data used in the empirical analysis. Section 3 presents our main empirical findings. Finally, Section 5 concludes.

1 A Simple Model of Adjustment Costs

In this section, we provide the theoretical motivation for the empirical analysis. To establish the theoretical link between labor hiring, and stock return and dividend predictability,

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

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

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

we consider a simplified version of the model in Belo et al. (2014) (henceforth BLB) who consider an economy with labor market frictions: labor hiring and firing is costly for firms, which is captured through an adjustment cost function.

1.1 Economic Environment

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

1.1.1 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 technology:

$$Y_t = Z_t X_t N_t^{\alpha}, \tag{1}$$

in which $0 < \alpha \leq 1$ 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

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

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:

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

in which $c_n^t = c_n^+ > 0$ if $H_t > 0$ and $c_n^t = c_n^- > 0$ if $H_t < 0$ are constants that control the size of labor adjustment costs.

1.1.2 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.

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

$$D_t = Y_t - W_t N_t - CN_t^{\text{adj}} \tag{4}$$

to be the dividend distributed by the firm to the shareholders. The dividend consists of output Y_t, less the wage bill $W_t N_t$, and labor adjustment costs CN_t^{adj}. 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

$$V(\mathbb{S}_t) = \max_{\{H_{t+j}, N_{t+j+1}\}_{j=0}^{\infty}} \left\{ \mathbb{E}_t \left[\sum_{j=0}^{\infty} M_{t,t+j} D_{t+j} \right] \right\}, \tag{5}$$

subject to the labor accumulation equation (2), and the flow of funds constraint (4) for all dates t.

1.1.3 Optimality Conditions

The first order condition for hiring H_t is given by:

$$q_t^N = c_n^t \frac{H_t}{N_t} \tag{6}$$

where q_t^N is the labor's marginal q.

The first order condition for the stock of labor N_{t+1} is given by:

$$q_t^N = E_t \left\{ M_{t+1} \left[\alpha Z_t X_t N_t^{\alpha-1} - W_{t+1} + \frac{c_n^t}{2} \left(\frac{H_{t+1}}{N_{t+1}} \right)^2 + (1-\delta_n) q_{t+1} \right] \right\} \tag{7}$$

To help intuition, suppose the production function has constant returns to scale (that is, $\alpha = 1$) and adjustment cost is symetric ($c_n^+ = c_n^- > 0$). In this case, both the production function and the adjustment cost function are homogeneous of degree of one, and hence the Hayashi (1982) conditions hold. This implies that the firm's stock price P_t (with P_t defined as $P_t \equiv V(\mathbb{S}_t) - D_t$) is given by:

$$P_t = q_t N_{t+1}. \tag{8}$$

That is, the value of the firm equals the value of the firms's instaled labor force. This value is given by the labor's marginal q (the shadow price of the labor force) times the size of the labor force.[6]

We can use the previous equation to establish a more clear link between the firm's hiring rate and discount rates. Following Kogan and Papanikolaou (2012) (in the context of physical capital investment), note that equations (6) and (8) imply that:

$$\ln c_n + \ln \frac{H_t}{N_t} = \ln \frac{P_t}{N_{t+1}} = \ln \frac{P_t}{D_t} - \ln \frac{D_{t+1}}{D_t} + \ln \frac{D_{t+1}}{N_{t+1}}. \tag{9}$$

Here, for simplicity, we are assuming that the gross hiring rate is always positive. Applying the Campbell and Shiller (1988) decomposition to the log of the price-dividend ratio:

$$\ln \frac{P_t}{D_t} \approx \text{const} + E_t \left[\sum_{j=1}^{\infty} \rho^{j-1} (\Delta \ln D_{t+j} - \ln R_{t+j}) \right], \tag{10}$$

[6]Hayashi (1982) provides a formal proof of this result in the context of one-capital good model (with physical capital instead of labor).

where $\rho = \frac{P/D}{1+P/D}$. Using the above two equations (9) and (10),

$$\ln \frac{H_t}{N_t} \approx \text{const} - \ln c_n + E_t \left[\ln \frac{D_{t+1}}{N_{t+1}} + \sum_{j=1}^{\infty} (\rho^j \Delta \ln D_{t+j+1} - \rho^{j-1} \ln R_{t+j}) \right]. \tag{11}$$

The equation expresses a relation between three endogenous variables: the optimal hiring rate, the expected future firm profitability (measured by firm's dividends relative to its labor stock, and also future dividend growth), and the expected future stock return.

1.2 Model Predictions

Equation (11) motivates our empirical analysis. This equation shows that, in the presence of labor adjustment costs, the firm's hiring rate H_t/N_t is a forward looking decision, containing information about the firm's future dividends ($\ln(D_{t+1}/N_{t+1})$, $\{\Delta \ln D_{t+j}\}_{j=2}^{\infty}$) and also about the firm's future (expected) stock returns $\{\ln R_{t+j}\}_{j=1}^{\infty}$. We investigate these links using standard (Fama and French (1989); Lettau and Ludvigson (2002)) short- and long-horizon predictive regressions of the form:

$$\Sigma_{h=1}^{H} y_{t+h} = a + b\text{HN}_t + \varepsilon_{it}, \tag{12}$$

in which $\Sigma_{h=1}^{H} y_{t+h}$ 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 firm's hiring rate. Using equation (11), the predicted variables considered are: (i) $y_t = r_{st} - r_{ft}$, in which r_t^s is the firm's log stock return, and r_{ft} is the log risk-free rate; (ii) $y_t = \Delta d_t$, in which Δd_t is the growth rate of dividends; and (iii) $y_t = \ln(D_t/N_t)_t$, is the dividend-to-labor ratio. Note that in terms of timing of the variables, equation (11) specifies that firm's current hiring rate is related to cumulated future dividends that start at time $t+2$ (not $t+1$) onward, and we impose this timing in the empirical analysis. In addition, the equation (11) links current the firm's current hiring rate to the next period dividend-to-labor ratio, but not beyond the first year. Thus, we do not look at longer horizon predictability for this variable.

Our analysis so far is silent about the level of aggregation of the firm in the model: we can interpret the firm as the aggregate firm, as a single firm, or as other level of aggregation. In the baseline case, we interpret the firm in the model as an aggregate firm. According to this interpretation, equation (11) provides a natural link between the aggregate hiring rate with both aggregate risk premiums and aggregate dividends in the time series. Here, the firm's dividend correspond to the aggregate dividends in the data, and the firm's risk premium corresponds to the expected excess return on the overall stock market.

In addition, we interpret the firm in the model as a low market beta or high market beta firm, in which case we examine the predictability of the hiring rate aggregated separately across firms with low market beta, and firms with high market beta market. We focus on these two groups of firms because they have different sensitivities to changes in the expected market excess return, which is the main variable of interest for our analysis. The reason is as follows. Consider a capital asset pricing model (CAPM) representation of equilibrium expected returns, in which the firm's risk premium is given by:

$$E_t[\ln R_{it+1}] = r_f + \beta_i E_t[r_{mt+1} - r_f], \tag{13}$$

in which $E_t[\ln R_{it}]$ is the firm's expected market return, r_{mt+1} is the log aggregate stock market return, and r_f is the log risk free rate (assumed here to be constant). $E_t[r_{mt+1} - r_t]$ is the market risk premium. The higher the market beta of a firm, the more sensitive the firm's risk premium is to the changes in the market risk premium. This observation has direct implications for the slope coefficients in the aggregate stock market return predictability regression (12). To develop some intuition, assume that the dividend predictability is small, and hence approximate expected dividends to be constant. In addition, assume that $E_t(\ln R_{t+j}) = r_t$

for $j = 1, ..., \infty$. Using some algebra, we can then re-write equation (11) as:[7]

$$E_t[r_{mt+1} - r_f] \approx \kappa - \frac{1-\rho}{\beta}\frac{H_t}{N_t}, \tag{14}$$

where κ is a constant. Thus, all else equal, the slope coefficient in the predictability regression 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 stock market risk premium $E_t[r_{mt+1} - r_f]$, 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 (that is, the same movement in the hiring rate in low and high market beta firms reveals a higher change in the aggregate stock market risk premium in low market beta firms, because of the lower sensitivity of the risk premium of these firms to the aggregate stock market risk premium).

Note that the previous analysis does not rely on the assumption that the CAPM in equation (13) is the right asset pricing model for asset returns. The previous intuition holds in any multi-factor model that includes the market excess return (the variable that we want

[7] We obtain this result as follows. Define the following variables:

$$\begin{aligned} E_t\left(\ln \frac{D_{t+1}}{N_{t+1}}\right) &= d/n \\ E_t(\Delta \ln D_{t+j+1}) &= x \text{ for } j = 1, 2, ... \end{aligned}$$

Similarly, assume that $E_t(\ln R_{t+j}) = r_t$. Substituting the previous definitions in equation (11) and using Taylor expansion around $\frac{H_t}{N_t} = 1$, implies

$$\frac{H_t}{N_t} - 1 \approx \text{const} - \ln c_n + d/n + \frac{\rho}{1-\rho}x - \frac{1}{1-\rho}r_t.$$

Finally, using the CAPM equation (13), and rearranging terms, we can write the previous equation as:

$$E_t[r_{mt+1} - r_f] \approx \kappa - \frac{1-\rho}{\beta}\frac{H_t}{N_t},$$

where κ is a constant given by $\kappa = -\frac{1-\rho}{\beta}\left[-1 - \text{const} + \ln c_n - d/n - \frac{\rho}{1-\rho}x + \frac{1}{1-\rho}r_f\right]$.

to forecast) as one of the factors. The important point for this analysis is the fact the we are looking at two set of firms that differ in their sensitivity to aggregate stock market risk premium, which is the variable we want to forecast.

In terms of dividend predictability, it is also important to note that in this market beta decomposition, equation (11) links the firm's hiring rate to its dividends, not aggregate dividends.

In addition to the low versus high market beta set of firm, we look at small and large firms (as measured by number of employees) and young versus old firms. The motivation is similar to the motivation for looking and different market beta firms. Because measuring market beta is difficult in practice, we look at other characteristics that are known to be associated with market beta. Small and young firms have higher market betas than large and older firms.

2 Empirical Procedures

This section describes the data used in the empirical analysis and the empirical specifications.

2.1 Data

The key variable for the empirical work is the labor hiring rate, and we measure this variable as in Davis, Faberman, and Haltiwanger (2006) and Bloom (2009). The hiring rate is given by

$$\mathrm{HN}_t = \frac{\mathrm{N}_t - \mathrm{N}_{t-1}}{0.5 \times (\mathrm{N}_{t-1} + \mathrm{N}_t)}$$

where N_t is employment. By construction, this measure of labor hiring is bounded by $\pm 200\%$. We obtain N_t from two sources: CRSP/Compustat Merged Annual Industrial Files, and from the Bureau of Labor Statistics Current Employment Statistics (BLS CES). The

Compustat data includes only publicly traded firms, while the BLE CES data includes all (public and private) furms in the economy. Thus, the use of these two data sources allows to study the relationship between hiring and both stock returns and dividends across publicly traded firms and also private firms in the economy. This analysis is motivated by the findings Chen and Zhang (2011) who find that employment growth of all (public and private) firms in the economy has only a mild predictability for stock returns and aggregate risk premium.

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 [8]. Besides, we correct for the delisting bias following the approach in Shumway (1997). We use data of aggregate risk premium from Kenneth French's website, and data of aggregate dividends from Robert Shiller's website.

We construct the hiring rate across firms with low and high market beta, small and

[8]We include financials and utilites. 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.

large, and young and old as follows. We classify a firm as high or low market beta firm based on the firm's past year market beta computed from CAPM regression at the montly frequency. A firm is defined as a high market beta firms if its market beta is above the NYSE 80% breakpoint[9] (results are similar if we use the median breakpoints; we focus on the 80^{th} percentile using the same rationale for the micro cap classification used in Fama-French, 2008). We classify Compustat firms as large firms and small firms based on the firm's last period size of the labor force (variable EMP), and define small firms as EMP below NYSE 20% breakpoint (again, we focus on the 20^{th} percentile following Fama and French (2008) definition of micro caps. We classify Compustat firms as young and old based on the number of years the firm has appeared in Compustat and using the median breakpoint. In all cases, we then compute the portfolio-level aggregate hiring rates for each group of firm, and we study how it predicts aggregate stock market excess returns, and its portfolio-level dividends.

2.2 Descriptive Statistics

Table 1 shows the descriptive statistics of hiring rates for public (Compustat) firms, all firms (CES, public and private), private firms, low and high market beta firms, small and large firms, and young and old firms.

[Table 1 here]

The correlation between the hiring of public firms and of all firms is high, about 78%. The difference is driven by the private firms: the correlation between the hiring of public and private firms is 41%, suggesting that there the hiring in these two groups of firms is not driven by the exact same set of factors. The mean and volatility of hiring of the public firms is also higher than both all firms and private firms. Figure 1 plots the time series of these three series.

[9] Note that market beta is negatively related to size.

[Figure 1 here]

Across the three sub-groups of firms, Table 1 shows that the hiring rate of high market beta, small, and young firms has a higher mean and are more volatile than the hiring rate of low market beta, large, and old firms.In addition, the table shows that the hiring rate of the public firms is mostly driven by the large, low market beta, old firms. The correlation between the aggregate hiring of public firms with the hiring rate of large, low market beta, and old firms is 97%, 94%, and 95%, respectively. The correlation between the aggregate hiring of public firms with the hiring rate of small, high market beta, and young firms is significantly smaller, 58%, 77%, and 72%, respectively. Figures 2 and 3 show the time series of the hiring rates across the size and market beta portfolios, together with the hiring rate of all public firms for comparison.

[Figures 2 and 3 here]

2.3 Empirical Specifications

We use standard short- and long-horizon predictive regressions described in equation (12). 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 forecasts and ENC-NEW encompassing test statistic from Clark and McCracken (2001). A negative out-of-sample R^2 means that the out-of-sample errors are larger than the errors obtained using the historical mean of the predicted variable (up to time t). For each regression, we compute the slope coefficient b in Equation (12), and the in-sample adjusted R^2.

3 Empirical Evidence

In this section, we document our main findings on the link between hiring, discount rates, and dividends in the time series.

3.1 Hiring and Aggregate Discount Rates

We first investigate the relationship between hiring and discount rates across public and private firms, and then across beta/size/age firms.

Public and private firms. Table 2 shows the aggregate stock return predictability results of the hiring rate of public, all, and private firms in the U.S economy. In all cases, the aggregate hiring rate predicts the aggregate stock market return with a negative slope. That is, hiring and aggregate discount rates are negatively related.

[Table 2 here]

The hiring rate of the public firms is more informative about aggregate risk premium in the economy than both the combination of public and private (all firms). At the three to five year horizon, the aggregate hiring rate of public traded firms shows good predicting power, with in-sample R^2 from 15% to 27% and an out-of-sample R^2 from 17% to 28%. The aggregate hiring rate of all firms in the economy shows only a modest predictability power of 11% in-sample R^2 at four year horizon, but all out-of-sample R^2 are insignificant at 10% level. This result is broadly consistent with the findings Chen and Zhang (2011) who document only a mild predictability power of employment growth of the aggregate hiring rate of all (public and private) firms in the economy.

The difference in the return predictability results across public and all firms in the economy suggest that the inclusion of the private firms in the measurement of aggregate hiring deteriorates the information content of the aggregate hiring rate for stock returns. Consistent with this interpretation, the results for the aggregate hiring across private firms in

Table 2 show that the hiring of private firms does not predict stock returns at any horizon. In the multivariate regressions using both private and all firms as predictors, the last panel in Table 2 shows that the slope coefficient associated with the hiring rate of public firms is significant at all horizons, while the slope coefficient for the hiring rate across all firms is only significant at the 1-year horizon (and its slope is positive, albeit insignificant, in contrast with the negative slope in the univariate regression case).

Chen and Zhang (2011) uses quarterly, not annual, CES data. To show that our results are not specific to the use of lower frequency data, we proceed as follows. Given that the employee data in Compustat is only available at annual frequency, we construct an hiring rate of public firms at the quarterly frequency by exploring the differences in the fiscal-year end across firms. Specifically, for each quarter, we use the subset of Compustat firms whose fiscal year end is at a month that falls in that quarter. We then construct a time series of the (annual) aggregate hiring rate of public firms at the quarterly frequency. We construct the hiring rate of all firms (in CES) at quarterly frequency using an analogous procedure, that is, compute the same quarter of year t–1 -to-quarter of year t employment growth.

[Table 3 here]

Table 3 shows the return predictability results using the hiring rate of the public firms and also of all firms (public and private) at quarterly frequency, ranging from 1 quarter horizon to 40 quarters. The in-sample and out-of-sample R^2 for both public and all firms first increase and then decreases, with the maximum R^2 achieved at 20 quarters. Although the difference in performance across the two set of firms is small at short horizons, the hiring rate of the public firms predicts risk premium significantly better than the hiring rate of all firms from at the 28 quarter horizon and beyond.

Beta/size/age firms. Table 4 shows the results for return predictions across beta/size/age portfolios. The results show that the return predictability of the aggregate hiring rate of public firms hiring rate comes mainly from large, low beta, and old firms. For example, at the 4-year horizon, all public firms with December sample has in-sample R^2 of 23.4% and an out-of-sample R^2 of 25.1% at 4 year horizon. For large firms, the corresponding $R^{2\prime}s$ are 22.8% and 24.4% versus 7.1% and 4.4% for small firms. For low beta firms, the corresponding R^2's are 27.4% and 30.7% versus 14.2% and 14.9% for high beta firms. And for old firms, the corresponding R^2's are 25.7% and 27.6% versus 4.8% and 1.0% for young firms.

[Table 4 here]

In addition, Table 4 shows that the estimated slope coefficients are significantly more negative for large/low beta/old firms than for small/high beta/young firms. For example, at the 4 year horizon, the slope coefficient associated with the hiring rate is -4.7 for large firms and only -0.94 for small firms. For low beta firms, the slope coefficient associated with the hiring rate is -5.4 versus -2.06 for high beta firms. And for old firms, the slope coefficient associated with the hiring rate is -5.1 versus -1.35 for high beta firms.

3.2 Hiring and Cash Flow Predictability

In this section we investigate the relationship between hiring and cash flow predictability both across public and private firms, and also across beta/size/age firms.

Public and private firms. Table 5 shows the aggregate dividend growth predictability results (starting in period 2 onwards, consistent with equation (11)) Both public and all firms hiring predict dividend growth negatively and they perform similarly well with in-sample and out-of-sample R^2 increasing over horizons. The hiring of private firms does not predict dividend growth. We note that in multivariate predictive regressions using both public firms and all firms hiring rate as predictors, both become insignificant mostly likely due to their high correlation.

[Table 5 here]

Turning to the analysis of the predictability of the one-year ahead aggregate dividend to labor ratio (consistent with equation (11). We focus on the public firms only because aggregate dividends refer to the dividends from firms, not private firms. Table 6 shows that the hiring rate of public firms predicts in-sample the one-year ahead aggregate dividend-to-labor ratio with an R^2 of 15.1%. The slope is positive, consistent with a holding all else constant interpretation of equation (11) in the model. The out-of-sample R^2 is significantly negative, however. That is, in out of sample analysis, the aggregate hiring rate predicts the aggregate dividend-to-labor ratio worse than the historic mean of the dividend-to-labor ratio. This result is in sharp contrast with the return predictability results in the previous section in which the aggregate hiring rate performs well both in-sample and out-of-sample.

[Table 6 here]

Beta/size/age firms. Equation (11) links the firm's hiring rate to its dividends, not necessarily to aggregate dividends, unless we interpret the firm as the aggregate firm. Thus, here, we do not examine the aggregate dividends predictability. Instead, we examine the predictability of the dividends of the each group of firms. For tractability, we focus here on results for the beta sorted portfolios because the results for the size and age portfolios are similar (results available upon request).

[Table 7 here]

Table 7 shows the results for dividend growth predictability (starting in year 2 onwards) across beta groups. The link between the hiring rate of low beta firms and its future dividends is weak, both in sample and out of sample. Across all the horizons the slope coefficient is insignificant and the in-sample regression R^2 are all below 5%. The out of sample R^2 are close to zero across all horizons (although it become 8% at the $5-$year horizon, but according to the ENC-NEW statistics we fail to reject the hypothesis that this R^2 is zero. The link between the hiring rate of high market beta firms and its future dividends is significantly stronger, both in sample and out of sample. Across all the horizons the slope coefficient is negative, and its statistically significant at the 2, 4, and 5 year horizons. The in-sample and out of sample regression R^2 at the 4- and 5-year horizon are both above 16%, Using the ENC-NEW statistics, we can reject the null hypothesis that the out of sample R^2 is zero across the 4 and 5−year horizons. Taken together, hiring and future dividend growth are significantly linked across high beta firms, but not across low beta firms. This results is in sharp contrast with the aggregate return predictability results, for which the hiring rate of the low beta firms was a significantly stronger predictor of aggregate return than the hiring rate of high beta firms.

Turning to the analysis of the predictability of the one-year ahead group-specific dividend to labor ratio, the bottom panels in Table 6 shows that, again, the link between the hiring rate of low beta firms and its future one-year ahead dividend-labor ratio is weak. The in-sample R^2 is 0.5% and its out of sample R^2 is negative. Also, the link between the hiring rate of high market beta firms and its future dividend-to-labor ratio is significantly stronger, both in sample and out of sample. The in-sample R^2 is 10.7% and its out of sample R^2 is 6.8%.

3.3 Is the Predictability Coming Directly from Hiring Rate or through its Relation to Cash Flow Growth?

Because the hiring of publicly traded firms shows both return and dividend growth predictability, a natural question to ask is, does return predictability come form dividend growth predictability?

Panel A of Table 8 addresses this concern. We use sales growth as a proxy for cash flow news. Specifically, we use the residuals of regressing hiring rates on aggregate sales growth to predict aggregate stock market excess returns in the first set of results. Clearly, the residual from this regression predicts aggregate excess returns fairly well. At the 4-year horizon, the hiring rate of public firms produces an in sample R^2 of 11.7% and an out of sample R^2 of 10.8%. At the 5−year horizon, the results are stronger. The hiring rate of public firms produces an in sample R^2 of 17.3% and an out of sample R^2 of 15.6%.

Its interesting to investigate the results inverting the previous relationship, that is, examine the predictive power of the component of sales growth that is not explained by the aggregate hiring rate. Specifically, we extract the residual from a regression of aggregate sales growth on the aggregate hiring rates. The second set of results shows this component has no predictability for aggregate stock market excess returns. Most in-sample R^2 are small and the slope coefficients are all insignificant.

Panel B of Table 8 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 the first set of results, for all public firms (December sample), hiring rate not explained by sales growth has mild predictability for dividend growth. As shown in the second set of results, sales growth rates not explained hiring rate show moderate predictability for all public firms (December sample). 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 8 here]

4 Quantitative Analysis

In this section we calibrate the model and evaluate the extent to which the model gives similar return predictability patterns to that observed in the data. We then use the model to provide an economic analysis of the mechanism.

4.1 Functional forms

Following Zhang (2005), we directly specify the stochastic discount factor without explicitly modeling the consumer's problem. The stochastic discount factor is given by:

$$\log M_{t,t+1} = \log \beta + \gamma_t (x_t - x_{t+1}) \tag{15}$$

$$\gamma_t = \gamma_0 + \gamma_1 (x_t - \bar{x}) \ , \tag{16}$$

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:

$$R_{f,t} = \frac{1}{E_t\left[M_{t,t+1}\right]} = \frac{1}{\beta} e^{-\gamma_t (1-\rho_x)(x_t - \bar{x}) - \frac{1}{2}\gamma_t^2 \sigma_x^2} \tag{17}$$

$$SR_t = \frac{\sigma_t\left[M_{t,t+1}\right]}{E_t\left[M_{t,t+1}\right]} = \sqrt{e^{\gamma_t^2 \sigma_x^2} - 1}. \tag{18}$$

Equation (15) 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 (16), 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).

4.2 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 ??. The return-to-scale parameter, α, is 0.7. 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. To calibrate the persistence parameter ρ_z and the conditional volatility parameter σ_z of the firm-specific productivity shock, we restrict these two parameters using their implications on the degree of dispersion in the cross-sectional distribution of firms' stock return volatilities. Thus we set $\rho_z = 0.97$ and $\sigma_z = 0.10$, implying an average annual volatility of individual stock returns of 39%, approximately the value of 32% reported in Vuolteenaho (2001). The labor adjustment cost parameter, c_n^+ is 10 and c_n^- is 100, matching the volatility of aggregate hiring rate. Wage rate is normalized to 1 in the benchmark calibration, which implies that the wage is rigid. We also experiment a different calibration of wage rate by setting is perfectly correlated with the aggregate productivity. We pin down the three parameters governing the stochastic discount factor, β, γ_0, and γ_1 in equation (15) and (16), by matching three aggregate return moments: the average real interest rate, the volatility of the real interest rate, and the average Sharpe ratio in the U.S economy (approximately 0.36). This procedure yields $\beta = 0.9999$, $\gamma_0 = 15$, and $\gamma_1 = -1000$. The model is simulated at monthly frequency and aggregated into annual frequency.

4.3 Main results

Baseline model

We replicate the empirical procedure for the predictive regressions using the simulated data from the benchmark model. The baseline model specification in table 9 reports the result. Aggregate hiring rate negatively predicts future stock market returns from year 1 to year 5 (with the slopes of -1.02 in year 1 and -2.27 in year 5), consistent with the data. In addition, aggregate hiring rate negatively predicts aggregate future dividend growth in year 1 with the slope of -0.26; however from year 2 to year 5, hiring rate does not predict future dividend growth.

Table 10 reports the predictability for future stock market returns and aggregate dividend growth across size groups. We see big firms' hiring rate has stronger predictability than small firms. The slopes of big firms' hiring rate in predicting future market returns ranges from -1.04 to -2.20 for year 1 and year 5, while the slopes of small firms are -0.16 to -1.09, an order of magnitude smaller. Similarly, big firms' predictability for aggregate dividend growth is also stronger than small firms. The slopes of big firms' hiring rate in predicting dividend growth is -0.26, 10 times bigger than those of small firms of -0.027. For year 2 to year 5, the predictability of dividend growth for small and big firms all become tiny and close to zero.

Inspecting mechanism

Next we inspect the model mechanism. Specifically we perform several comparative statics analyses to show the economic forces driving the overall good fit of the model. We consider three additional model specifications:

- A model with constant price of risk ($\gamma_1 = 0$)
- A model with wage rate set to perfectly correlated with aggregate productivity $W_t = X_t$ (no wage rigidity)
- A model with frictionless labor adjustment (zero labor adjustment cost; $c_n^+ = c_n^- = 0$)

Model specifications 2 to 4 in table 9 present the results. When we shut down the time-varying price of risk (model specification 2), the aggregate hiring rate predictability for future stock market returns drop substantially (-1.02 to -2.27 in benchmark for year 1 to year 5 vs. -0.30 to 0 now). The predictability for future aggregate dividend growth drop as well (-0.26 in the benchmark vs. -0.08 now for year 1). Moreover, the predictability of hiring rates cross size group also disappear (Table 10). For example, big firms' hiring rate now has slopes close to zero in predicting future market returns; small firms' slopes become tiny and insignificant. The slopes of big and small firms' hiring rates in predicting aggregate dividend growth are -0.30 and -0.07, similar to those the benchmark model.

When we turn off wage rigidity (model specification 3), we see that the slope of aggregate hiring rate in predicting future stock market returns becomes positive, opposite to the data. This happens because by turning off wage rigidity, wages are perfectly correlated with the aggregate productivity risk, making it a hedge. Thus quantity of risk becomes procyclical, leading to positive predictability for future market returns. In addition, small firms' hiring rate has much stronger predictability than big firms (positive actually), counterfactual to the data. This happens because without wage rigidity, small firms are those with low productivity and have more volatile quantity of risk than big firms. Turning to dividend predictability, both small and big firms' hiring rates positively predict 1 year head aggregate dividend growth, then become negative and close to zero.

Lastly we shut down the labor adjustment costs (model specification 4). The aggregate hiring rate predictability for future stock returns drops significantly (-1.02 to -2.27 in benchmark for year 1 to year 5 vs. -0.37 to -1.20 now). This is intuitive, without labor adjustment costs, firms will be able to reach their optimal hiring targets, thus quantity of risk does not vary as much as in the benchmark model. Turning to the predictability across size groups, small firms' slopes in predicting future market returns are -0.16 to -0.41, smaller than those of big firms of -0.37 and -1.15, consistent with the data. This happens because wage rigidty makes hiring rate predictability stronger for big firms. However, both small and big firms' predictability drop significantly compared to the benchmark model. Lastly, the hiring rate predictability for future aggregate dividend growth drop substantially close to zero for both small and big firms.

Taken together, we find that both time-varying price of risk and time-varying quantity of risk are necessary to generate stock market return and dividend predictability observed in the data. Furthermore, labor market frictions, e.g., both wage rigidity and labor adjustment costs are important to generate time-varying quantity of risk in the model jointly. Lastly, wage rigidity is also important to generate the predictability of stock market returns and dividend growth by small and big firms' hiring rates.

5 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, both in-sample and out-of-sample. 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 low beta/large/older firms than in high beta/small/young firms. Because private firms tend to be smaller and younger 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, but the dividend predictability is not the main driver of the return predictability. Taken together, our results demonstrate the significance of labor hiring to understand the dynamic nature of aggregate discount rates and cash flows.

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Table 1
Summary Statistics

This table reports descriptive statistics for the hiring rate series used in the empirical tests. Panel A reports statistics for broad samples of firms. *Public* is the hiring rate calculated from all firms in the Compustat sample. *All* is the hiring rate calculated from firms in the CES/BLS sample. *Priv* is hiring rate for private firms calculated from the difference in employment between the Compustat and CES/BLS samples. *Public (Dec)* is the hiring rate of firms in Compustat with fiscal year ending in December. Panel B reports statistics for subsamples of firms from the *Public (Dec)* sample. *High Emp* and *Low Emp* denote the hiring rates of the portfolios of firms sorted on lagged number of employees *Low Beta* and *High Beta* denote the hiring rates of the portfolios of firms sorted on lagged conditional market betas constructed over 12 months and Dimson corrected. *Old Firms* and *Young Firms* denote the hiring rates of the portfolios of firms formed on the number of years they first appeared in the Compustat sample. The breakpoints for *High Emp* and *Low Emp*, for *Low Beta* and *High Beta*, and for *Old Firms* and *Young Firms* are the first quintile of the respective variable from the sample of NYSE firms. The sample period is 1963 to 2015.

				Correlations									
Series	Mean	Std	Auto Corr	Public	All	Priv.	Public (Dec)	High Emp	Low Emp	Low Beta	High Beta	Old Firms	Young Firms
Panel A: Broad Samples													
Public	2.90	2.85	0.52	1.00	0.41	0.78	0.98	0.97	0.58	0.94	0.77	0.95	0.73
Private	1.56	2.36	0.47	0.41	1.00	0.80	0.40	0.40	0.21	0.34	0.40	0.39	0.45
All	1.77	2.11	0.45	0.78	0.80	1.00	0.76	0.76	0.43	0.69	0.68	0.74	0.67
PublicDec	2.31	2.96	0.50	0.98	0.40	0.76	1.00	1.00	0.58	0.97	0.79	0.98	0.70
Panel B: *Public (Dec)* Subsamples													
High Emp	2.02	2.92	0.50	0.97	0.40	0.76	1.00	1.00	0.53	0.97	0.79	0.99	0.68
Low Emp	11.31	8.23	0.34	0.58	0.21	0.43	0.58	0.53	1.00	0.54	0.46	0.48	0.70
Low Beta	2.19	2.82	0.43	0.94	0.34	0.69	0.97	0.97	0.54	1.00	0.63	0.96	0.64
High Beta	2.53	5.25	0.38	0.77	0.40	0.68	0.79	0.79	0.46	0.63	1.00	0.79	0.56
Old Firms	1.61	2.94	0.49	0.95	0.39	0.74	0.98	0.99	0.48	0.96	0.79	1.00	0.58
Young Firms	6.68	4.74	0.51	0.73	0.45	0.67	0.70	0.68	0.70	0.64	0.56	0.58	1.00

Table 2
Aggregate Discount Rate Predictability by Broad Hiring Rate Series

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 horizons ranging from 1 year to 5 years. Predictor variables are aggregate hiring rate from Compustat (Public Firms), private firms (Private Firms), and CES (All Firms) and are described in Table 1. 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-val* denotes in-sample p-values constructed as in Newey and West (1987). ENC^{NEW} denotes the *New Encompassing* out-of-sample test statistic from Clark and McCracken (2001), following the construction methodology described in Kelly and Pruitt (2013).

Hiring Rate Series	Horizon	In Sample					Out of Sample	
			Series 1		Series 2			
		R^2	Coeff	p-val	Coeff	p-val	R^2	ENC^{NEW}
Public Firms	1	4.08	-1.23	0.07			0.34	0.45
	2	4.14	-1.73	0.09			3.80	0.50
	3	6.92	-2.43	0.02			7.28	0.62
	4	15.64	-3.97	0.00			17.57	1.39
	5	26.56	-5.80	0.00			27.50	2.46
Private Firms	1	0.56	-0.55	0.48			-0.48	-0.03
	2	0.02	-0.15	0.87			-4.42	-0.28
	3	0.00	-0.02	0.99			-10.59	-0.42
	4	0.04	-0.25	0.91			-13.77	-0.46
	5	0.01	-0.17	0.95			-8.55	-0.28
All Firms	1	2.01	-1.17	0.23			-0.75	0.17
	2	0.72	-0.98	0.38			0.12	0.02
	3	1.17	-1.35	0.30			-1.47	-0.08
	4	4.95	-3.02	0.10			2.69	0.15
	5	8.68	-4.54	0.02			7.81	0.48
Public, Private	1	4.09	-1.26	0.14	0.08	0.93	-1.92	0.15
	2	4.75	-2.04	0.07	0.89	0.36	-0.39	0.12
	3	8.36	-2.95	0.00	1.48	0.32	-1.22	0.15
	4	18.22	-4.72	0.00	2.15	0.27	7.77	0.88
	5	32.00	-7.06	0.00	3.62	0.05	25.77	2.42

Table 3
Aggregate Discount Rate Predictability by Broad Hiring Rate Series (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-val* denotes in-sample p-values constructed as in Newey and West (1987). ENC^{NEW} denotes the *New Encompassing* out-of-sample test statistic from Clark and McCracken (2001), following the construction methodology described in Kelly and Pruitt (2013).

Hiring Rate Series	Horizon	In Sample R^2	In Sample Coeff	In Sample p-val	Out of Sample R^2	Out of Sample ENC^{NEW}
Public Firms	1	0.29	-0.19	0.213	-1.25	-0.156
	2	0.40	-0.31	0.189	-0.30	0.122
	4	2.07	-0.73	0.077	2.33	0.638
	8	2.98	-1.18	0.015	4.71	0.508
	12	6.78	-2.00	0.001	8.27	0.660
	16	14.15	-3.15	0.000	14.84	1.069
	20	18.33	-3.96	0.000	17.60	1.168
All Firms	1	0.43	-0.40	0.180	-1.72	-0.246
	2	1.08	-0.78	0.139	-2.30	-0.139
	4	1.59	-1.25	0.130	0.54	0.308
	8	1.36	-1.63	0.161	1.45	0.140
	12	3.54	-2.81	0.049	3.33	0.236
	16	10.11	-5.04	0.002	10.09	0.683
	20	13.70	-6.47	0.001	13.36	0.828

Table 4
Aggregate Discount Rate Predictability by Portfolio Hiring Rate

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 horizons of 1, 3, and 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-val* denotes in-sample p-values constructed as in Newey and West (1987). ENC^{NEW} denotes the *New Encompassing* out-of-sample test statistic from Clark and McCracken (2001), following the construction methodology described in Kelly and Pruitt (2013).

Hiring Rate	Horizon	In Sample			Out of Sample	
Series		R^2	Coeff	p-val	R^2	ENC^{NEW}
High Emp	1	3.97	-1.18	0.08	-0.57	0.36
Firms	3	6.14	-2.23	0.02	6.86	0.59
	5	28.83	-5.92	0.00	31.16	2.78
Low Emp	1	0.04	-0.04	0.86	-2.41	-0.27
Firms	3	0.07	-0.08	0.84	-3.68	-0.21
	5	6.84	-1.02	0.01	2.38	0.23
Low Beta	1	6.87	-1.61	0.02	1.23	0.89
Firms	3	6.07	-2.30	0.03	6.45	0.58
	5	36.64	-6.97	0.00	40.65	4.25
High Beta	1	0.23	0.16	0.69	-2.09	-0.17
Firms	3	3.00	-0.87	0.11	3.18	0.26
	5	7.96	-1.72	0.03	5.24	0.43
Old	1	4.65	-1.27	0.07	1.15	0.68
Firms	3	7.82	-2.51	0.01	9.35	0.86
	5	31.91	-6.20	0.00	35.46	3.54
Young	1	0.58	-0.28	0.55	-12.73	-0.89
Firms	3	0.01	-0.05	0.96	-7.92	-0.42
	5	5.91	-1.64	0.08	0.61	0.38

Table 5
Aggregate Dividend Growth Predictability by Portfolio Hiring Rate

This table reports in-sample and out-of-sample R^2 for OLS predictions of aggregate real dividend growth (from Robert Shiller's website) from 1963 to 2015 across horizons ranging from 2 year to 5 years. Predictor variables are aggregate hiring rate from Compustat (Public Firms), CES (All Firms), and 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-val* denotes in-sample p-values constructed as in Newey and West (1987). ENC^{NEW} denotes the *New Encompassing* out-of-sample test statistic from Clark and McCracken (2001), following the construction methodology described in Kelly and Pruitt (2013).

Hiring Rate	Horizon	In Sample					Out of Sample	
Series			Series 1		Series 2			
		R^2	Coeff	p-val	Coeff	p-val	R^2	ENC^{NEW}
Public Firms	2	20.48	-1.63	0.00			17.42	2.12
	3	23.43	-2.25	0.00			21.43	2.03
	4	26.34	-2.69	0.00			22.55	2.08
	5	26.88	-2.80	0.00			15.59	1.52
Private Firms	2	8.71	-1.28	0.06			4.14	0.36
	3	10.81	-1.85	0.11			1.69	0.13
	4	11.23	-2.12	0.17			-1.89	-0.07
	5	6.72	-1.74	0.27			-3.74	-0.16
All Firms	2	19.98	-2.17	0.00			18.23	2.13
	3	24.82	-3.13	0.00			23.20	2.14
	4	30.94	-3.94	0.00			29.46	2.84
	5	31.87	-4.17	0.00			34.22	3.39
Public, Private	2	21.81	-1.44	0.00	-0.55	0.39	13.73	1.66
	3	25.34	-1.95	0.00	-0.85	0.42	13.65	1.27
	4	28.07	-2.37	0.00	-0.92	0.51	10.26	1.01
	5	27.04	-2.70	0.01	-0.29	0.82	2.69	0.64

Table 6
Portfolio Dividend-to-Labor Ratio Predictability by Portfolio Hiring Rate

This table reports in-sample and out-of-sample R^2 for OLS predictions of one-year ahead dividend-to-ratio ratios of portfolios of firms formed by number of employees, conditional market beta, and firm age, all of which are described in Table 1. Predictor variables are hiring rates of firms in the portfolio. 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-val* denotes in-sample p-values constructed as in Newey and West (1987). ENC^{NEW} denotes the *New Encompassing* out-of-sample test statistic from Clark and McCracken (2001), following the construction methodology described in Kelly and Pruitt (2013).

Hiring Rate	In Sample			Out of Sample	
Series	R^2	Coeff	p-val	R^2	ENC^{NEW}
Public	15.1	3.13	0.00	-48.0	-0.09
High Emp Firms	3.69	-0.06	0.08	6.38	1.16
Low Emp Firms	0.24	-0.04	0.72	-2.89	-0.32
Low Beta Firms	5.18	-0.07	0.04	9.98	1.86
High Beta Firms	1.27	-0.06	0.42	-1.51	-0.13
High Age Firms	5.39	-0.07	0.04	9.24	1.78
Low Age Firms	0.14	0.02	0.76	-3.77	-0.22

Table 7
Portfolio Dividend Growth Predictability by Portfolio Hiring Rate

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 of portfolios sorted on market beta (which is calculated using past 12 months with Dimson correction). *Low (High) Beta* stands for the hiring rate of low (high) market beta portfolio. The breakpoint for Low Beta is the first quintile of the respective variable from the sample of NYSE firms.

Hiring Rate		In Sample			Out of Sample	
Series	Horizon	R^2	Coeff	p-val	R^2	ENC^{NEW}
Low Beta	1	0.11	-0.18	0.79	-1.50	-0.16
Firms	2	0.24	-0.33	0.77	-1.99	-0.18
	3	1.61	0.95	0.40	2.97	0.34
	4	9.89	2.46	0.02	16.88	1.74
	5	8.98	2.41	0.02	15.20	0.96
High Beta	1	3.60	-1.48	0.13	0.05	1.48
Firms	2	4.85	-1.94	0.09	1.12	0.92
	3	13.99	-3.70	0.00	13.22	0.39
	4	12.49	-3.77	0.00	8.83	0.92
	5	7.49	-2.95	0.12	5.82	0.39

Table 8
Is the Predictability Coming From 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) and aggregate dividend growth (from Robert Shiller's website) from 1963 to 2015 across various horizons ranging from 1 to 5 years. Predictor variables are residuals of annual hiring rates or residuals of sales growth rates of public 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-val* denotes in-sample p-values constructed as in Newey and West (1987). ENC^{NEW} denotes the *New Encompassing* out-of-sample test statistic from Clark and McCracken (2001), following the construction methodology described in Kelly and Pruitt (2013).

	In Sample			Out of Sample	
Horizon	R^2	Coeff	p-val	R^2	$\mathrm{ENC}^{\mathrm{NEW}}$
Panel A: Return Predictability					
Predictor: Component of Hiring Rate Orthogonal to Sales Growth					
1	0.18	0.28	0.76	-1.71	-0.18
2	0.47	-0.63	0.60	-1.03	-0.07
3	4.32	-2.22	0.17	3.73	0.27
4	11.70	-4.10	0.03	10.79	0.71
5	17.25	-5.52	0.01	15.64	1.02
Predictor: Component of Sales Growth Orthogonal to Hiring Rate					
1	4.24	-0.69	0.12	8.48	1.48
2	3.24	-0.85	0.08	4.14	0.40
3	3.39	-1.02	0.06	2.76	0.19
4	3.35	-1.16	0.19	-0.98	-0.04
5	0.99	-0.70	0.51	-7.35	-0.27
Panel B: Dividend Growth Predictability					
Predictor: Component of Hiring Rate Orthogonal to Sales Growth					
1	2.54	0.38	0.14	2.34	0.33
2	0.02	-0.05	0.92	-2.15	-0.14
3	1.98	-0.77	0.28	-0.91	0.01
4	5.82	-1.49	0.06	3.92	0.31
5	9.05	-1.92	0.03	6.33	0.50
Predictor: Component of Sales Growth Orthogonal to Hiring Rate					
1	3.25	-0.22	0.07	0.28	0.20
2	3.92	-0.43	0.06	1.94	0.20
3	3.65	-0.54	0.11	2.76	0.19
4	3.48	-0.61	0.15	2.48	0.15
5	6.56	-0.86	0.10	4.76	0.30

Table 9
Aggregate hiring rate, stock return and dividend predictability

This table reports the predictability of stock market returns and dividend growth by aggregate hiring rate. There are four model specifications: 1). baseline model; 2) constant price of risk ($\gamma_1 = 0$); 3). a model without wage rigidity; and 4) a model without labor adjustment costs. The reported statistics in the model are averages from 100 samples of simulated data, each with 3000 firms and 600 monthly observations. We report the cross-simulation averaged annual moments. b is the slope coefficient, [t] is Newey-West adjusted t-statistics, and R^2 is adjusted R^2.

	1. Baseline			2. Constant price of risk			3. No wage rigidity			4. No Adjustment Costs		
	b	$[t]$	R^2	b	$[t]$	R^2	b	$[t]$	R^2	b	$[t]$	R^2
	Panel A: Return's predictability											
1	-1.025	-3.695	0.016	0.015	0.049	-0.003	1.464	1.576	0.005	-0.369	-1.500	0.004
2	-1.504	-3.098	0.022	-0.323	-0.526	-0.002	1.644	1.398	0.003	-0.128	-0.438	-0.002
3	-1.552	-2.784	0.017	-0.339	-0.433	-0.002	1.544	1.106	0.001	-0.642	-1.936	0.005
4	-1.392	-2.561	0.010	-0.362	-0.401	-0.002	3.092	2.042	0.008	-0.959	-2.803	0.012
5	-2.266	-3.707	0.028	0.184	0.190	-0.002	4.324	2.462	0.014	-1.193	-3.208	0.018
	Panel B: Dividend's predictability											
1	-0.259	-4.504	0.032	-0.298	-4.611	0.036	-0.425	-4.811	0.046	-0.120	-3.047	0.020
2	0.004	1.398	0.003	0.003	0.730	-0.001	0.000	-0.010	-0.003	-0.004	-2.198	0.017
3	0.000	0.491	-0.002	0.000	-0.579	-0.002	0.000	-0.719	-0.001	0.000	-1.286	0.000
4	0.000	-1.564	0.004	0.000	-0.505	-0.002	0.000	-0.783	-0.001	0.000	0.805	-0.001
5	0.000	0.807	-0.002	0.000	1.068	-0.001	0.000	0.078	-0.003	0.000	0.370	-0.002

Table 10

Stock market return and dividend predictability by size groups

This table reports the predictability of stock market returns and dividend growth by the hiring rates of small and big firms sorted by employees. There are four model specifications: 1). baseline model; 2) constant price of risk ($\gamma_1 = 0$); 3). a model without wage rigidity; and 4) a model without labor adjustment costs. The reported statistics in the model are averages from 100 samples of simulated data, each with 3000 firms and 600 monthly observations. We report the cross-simulation averaged annual moments. b is the slope coefficient, [t] is Newey-West adjusted t-statistics, and R^2 is adjusted R^2.

	1. Baseline			2. Constant price of risk			3. No wage rigidity			4. No adjustment costs		
	b	$[t]$	R^2	b	$[t]$	R^2	b	$[t]$	R^2	b	$[t]$	R^2
Small firms												
Panel A: Return's predictability												
1	-0.158	-0.867	-0.001	0.100	0.446	-0.002	-0.506	-2.533	0.006	-0.161	-1.414	0.002
3	-0.514	-1.772	0.003	0.326	1.004	-0.001	-0.202	-0.635	-0.002	-0.360	-2.586	0.007
5	-1.093	-3.445	0.017	0.383	0.868	-0.001	-0.713	-2.011	0.002	-0.410	-2.900	0.006
Panel B: Dividend predictability												
1	-0.027	-0.767	-0.002	-0.066	-1.513	0.003	-0.032	-1.101	0.000	-0.001	-0.046	-0.003
3	0.000	-0.597	-0.001	0.000	-0.599	-0.002	0.000	1.262	0.001	0.000	-0.552	-0.002
5	0.000	-0.006	-0.003	0.000	0.840	-0.001	0.000	0.872	-0.001	0.000	-1.654	0.003
Big firms												
Panel C: Return's predictability												
1	-1.037	-3.739	0.017	-0.001	-0.003	-0.003	1.605	1.822	0.007	-0.371	-1.514	0.004
3	-1.544	-2.825	0.017	-0.402	-0.520	-0.002	1.492	1.159	0.001	-0.625	-1.914	0.005
5	-2.198	-3.645	0.026	0.139	0.147	-0.003	4.330	2.612	0.017	-1.155	-3.125	0.017
Panel D: Dividend's predictability												
1	-0.264	-4.588	0.034	-0.297	-4.628	0.037	-0.378	-4.591	0.041	-0.124	-3.161	0.022
3	0.000	0.558	-0.002	0.000	-0.552	-0.002	0.000	-0.873	-0.001	0.000	-1.279	0.000
5	0.000	0.819	-0.002	0.000	0.991	-0.001	0.000	-0.083	-0.003	0.000	0.555	-0.002

Table 11
Stock market return and dividend predictability by beta groups

This table reports the predictability of stock market returns and dividend growth by the hiring rates of low and high CAPM betas. There are four model specifications: 1). baseline model; 2) constant price of risk ($\gamma_1 = 0$); 3). a model without wage rigidity; and 4) a model without labor adjustment costs. The reported statistics in the model are averages from 100 samples of simulated data, each with 3000 firms and 600 monthly observations. We report the cross-simulation averaged annual moments. b is the slope coefficient, [t] is Newy-West adjusted t-statistics, and R^2 is adjusted R^2.

	1. Baseline			2. Constant price of risk			3. No wage rigidity			4. No adjustment costs		
	b	$[t]$	R^2	b	$[t]$	R^2	b	$[t]$	R^2	b	$[t]$	R^2
Low beta firms												
Panel A: Return's predictability												
1	0.002	0.080	-0.003	-0.020	-0.520	-0.002	-0.015	-0.758	-0.001	-0.001	-0.086	-0.003
3	-0.004	-0.190	-0.003	-0.041	-0.755	-0.002	-0.020	-0.906	-0.001	-0.029	-1.799	0.002
5	0.013	0.595	-0.002	-0.003	-0.047	-0.003	-0.034	-1.480	0.000	-0.009	-0.492	-0.002
Panel B: Dividend's predictability												
1	-0.006	-1.970	0.005	-0.007	-0.888	-0.001	0.001	0.518	-0.002	-0.004	-1.634	0.004
3	0.000	0.582	-0.002	0.000	-0.734	-0.002	0.000	1.535	0.006	0.000	0.052	-0.003
5	0.000	0.544	0.000	0.000	0.171	-0.003	0.000	-1.258	0.000	0.000	-0.133	-0.003
High beta firms												
Panel C: Return's predictability												
1	-0.031	-0.638	-0.001	0.082	0.593	-0.002	0.045	0.841	-0.001	-0.015	-0.471	-0.002
3	-0.020	-0.390	-0.002	0.050	0.197	-0.003	0.059	1.013	-0.001	0.047	1.131	-0.001
5	-0.080	-1.378	0.000	0.048	0.156	-0.003	0.112	1.864	0.001	-0.015	-0.338	-0.002
Panel D: Dividend's predictability												
1	0.009	1.090	0.000	-0.046	-1.400	0.003	-0.004	-0.772	-0.001	0.009	1.649	0.003
3	0.000	-0.520	-0.002	0.000	0.116	-0.003	0.000	-1.723	0.009	0.000	-0.270	-0.002
5	0.000	-0.579	0.000	0.000	0.327	-0.002	0.000	1.048	-0.001	0.000	0.061	-0.003

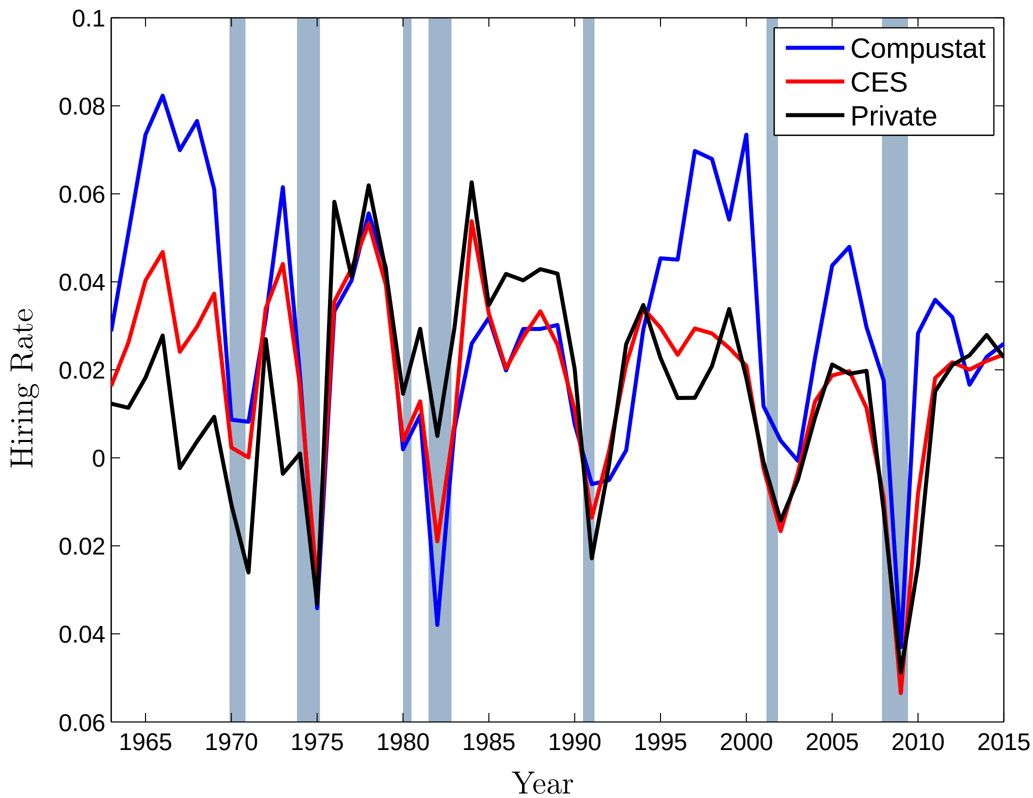

Figure 1. Aggregate Hiring Rates: Public Firms vs Private Firms vs All Firms. This figure shows the aggregate hiring rates from Compustat (i.e., "Public Firms"), from the Current Employment Statistics (CES) and from Bureau of Labor Statistics (i.e., "All Firms"), and from the difference in hiring from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

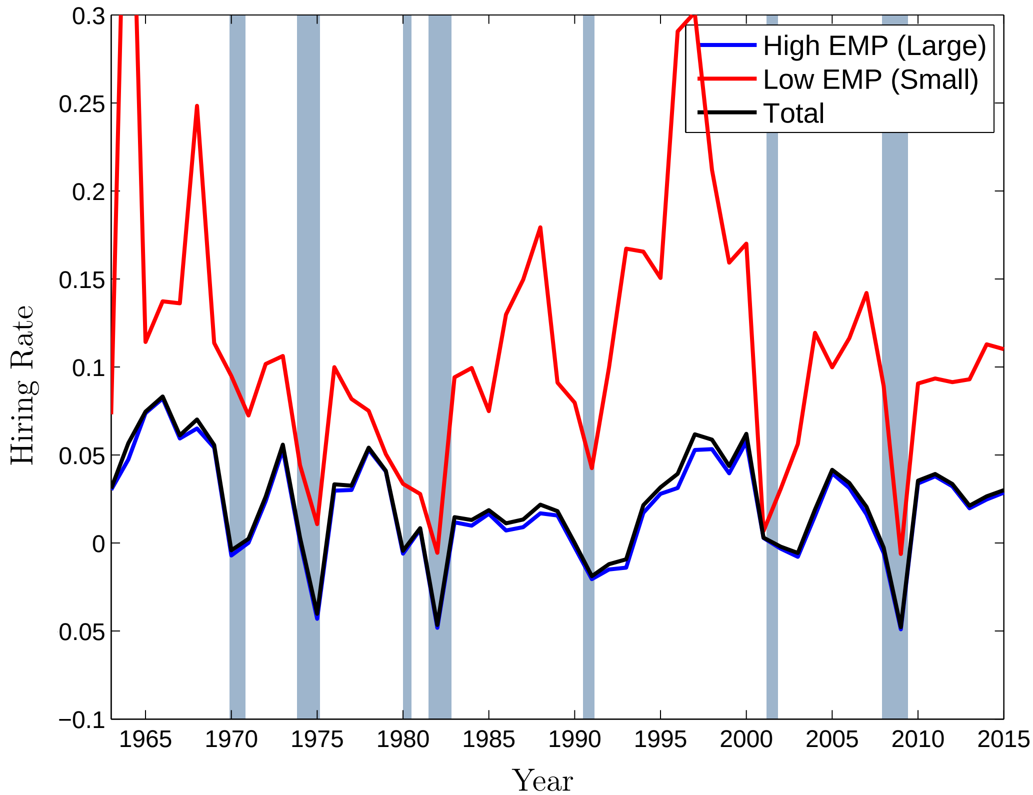

Figure 2. Hiring Rates for Subsamples of Public Firms Sorted by Number of Employees. This figure shows the hiring rates for the sample of firms in Compustat ("Total"), and of the subsamples of firms sorted on the number of employees. The "High Employment" subsample is defined by the NYSE 20% breakpoint. 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.

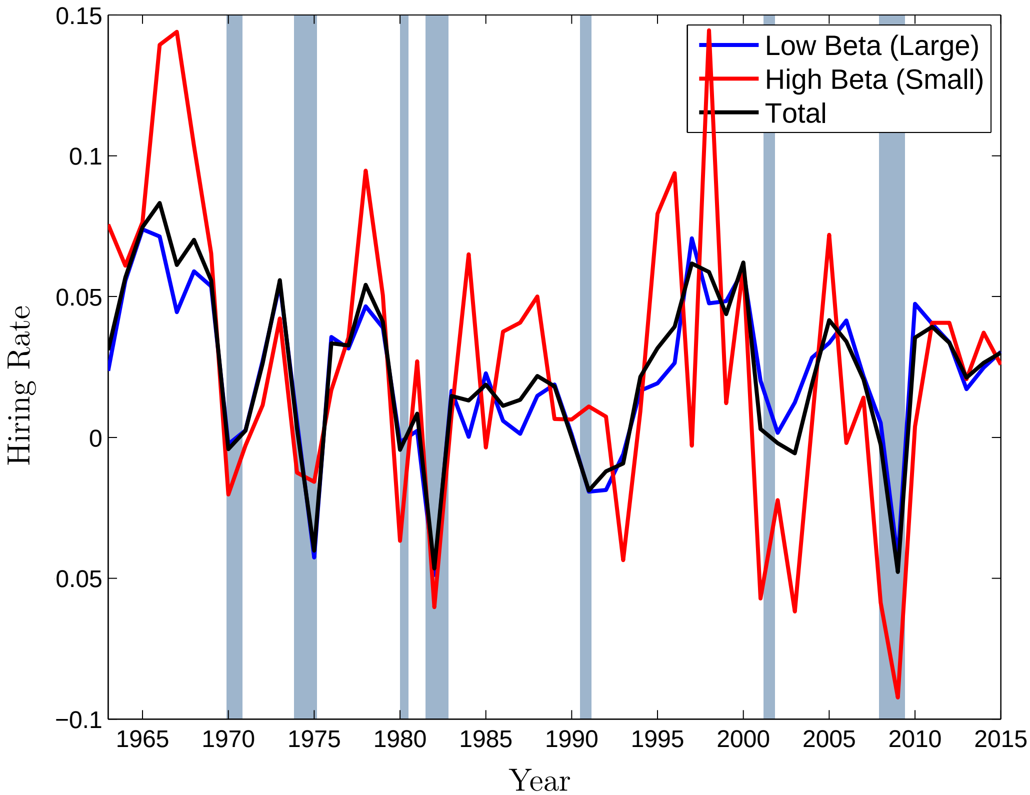

Figure 3. Hiring Rates for Subsamples of Public Firms Sorted by Conditional Market Betas. This figure shows the hiring rates for the sample of firms in Compustat ("Total"), and of the subsamples of firms sorted on the conditional market factor loadings. The "Low Beta" subsample is defined by the NYSE 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.